

## Review

# Advantages and Limitations of Measurement Methods for Assessing Odour Nuisance in Air—A Comparative Review

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**Abstract:** The odour quality of atmospheric air plays an important role in the comfort of life and human health. Odours can originate from various sources, including municipal facilities, the agricultural and food sectors or industrial plants. A holistic approach to reducing the formation and emission of odorous substances should therefore include the development of odour-neutral process solutions, deodorisation techniques and analytics to measure and monitoring such pollutants in the atmosphere. The implementation of appropriate measures in these three areas can enable the effective management and control of odour emissions. The aim of the work is to carry out a comparative analysis of current methods for measuring the content of odorous substances in the air and for monitoring this type of pollutant. The characterisation of existing solutions carried out became the basis for determining the strengths and weaknesses of the applied protocols and indicating the directions for their further development and improvement.

**Keywords:** malodorous substances; odour measurement; electronic nose; olfactometry; field studies; odour detection threshold; odour concentration; odour hours



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## 1. Introduction

The odour quality of atmospheric air plays a key role in shaping people's comfort and health [1]. Unpleasant odours, commonly referred to as smells or malodorous substances, can come from a variety of sources. These include municipal facilities such as sewage treatment plants, pumping stations, cesspools and retention basins, lagoons and sedimentation fields, stabilisation chambers, waste collection and storage facilities, mechanical and biological waste treatment plants, sorting plants, composting plants, landfills and many others [2,3]. Odour-emitting substances can also be emitted from economic activities, including agricultural and industrial activities [4]. In the agri-food sector, odours are generated and emitted from poultry farms, including chicken and turkey houses, pig farms, slurry tanks, manure storage facilities, fields fed with natural fertilisers, agricultural and utility biogas plants, digestate processing and storage facilities and many others [5]. As a result of technological and production processes, industrial plants emit a long list of chemical substances that negatively affect the expected standards of odour quality in the air, either directly or as a result of their transformation in the atmosphere [6].

Many countries have not introduced emission standards that would clearly define the method for monitoring the amount of odorous substances in the air and introduce metric units to describe their concentrations and the applicable reference values [7]. Despite the fact that such legal regulations are not binding, in many cases the ecological awareness of operators of facilities that have a significant impact on the emission of odorous substances

prompts their actions to reduce the negative impact on the environment [8]. In the context of efficiently solving problems related to odour immission, the availability of deodorisation techniques is important on the one hand, and simple, reliable and universal methods for determining the effectiveness of the applied solutions on the other [9]. Such a holistic approach to reducing the formation and emission of odorous substances should therefore include the development of odour-neutral process solutions, deodorisation techniques and analytics related to the measurement and monitoring of such pollutants in the atmosphere [10]. The implementation of appropriate measures in these three areas can enable the effective management and control of odour emissions.

The aim of this work is to carry out a comparative analysis of the methods available on the market for measuring the content of odorous substances in the air and to ensure the monitoring of this type of pollution. The characterisation of existing solutions carried out became the basis for determining the strengths and weaknesses of the protocols used and indicating directions for their further development and improvement.

## 2. Sources of Odorous-Intensive Gases

The adverse effects of foul-smelling gases on the comfort of life and human health have a direct impact on the complaints and demands of residents who live near the emission sources and are directly exposed to their effects. The most frequently cited sources of unpleasant odours and facilities that are perceived by residents as a permanent nuisance include the following:

- sewage treatment plants, which account for 30–40% of the reported complaints depending on the country, including grate and screening halls, trickling filters, sludge lagoons, collection points, sewage sludge treatment rooms, sewage sludge stabilisation and neutralisation plants and open biological reactors [11–13];
- industrial production facilities, which are estimated to account for 25–35% of odour complaints, including phosphoric acid production, nitrogen fertiliser production, textile and fibre industry processes, rubber production and processing, refinery processes, paint shops and the cellulose industry [14–16];
- agriculture and animal husbandry, which account for 15 to 25% of the reported complaints about odour emissions from poultry farms, including chicken and turkey houses, pig farms, slurry tanks, manure storage facilities, fields fed with natural fertilisers, agricultural and utility biogas plants, digestate processing and storage facilities and many others [17–19];
- municipal solid waste landfills, which are mentioned in 10–15% of the reported complaints about old facilities where selective waste collection was not performed, leading to uncontrolled anaerobic biochemical processes that cause the emission of hydrogen sulphide, methane, ammonia and other foul-smelling substances [20–22];
- the transport and storage of chemical substances account for about 10% of reported complaints [23–25].

Due to the existing objections of the local population to facilities that pose a risk of odour emissions and due to increasing social environmental awareness, it is necessary to take measures to reduce odour nuisance. Table 1 shows the most important types of chemical compounds whose emission and presence in the air in certain concentrations determine the odour nuisance of various municipal facilities and industrial plants.

**Table 1.** Selected chemical compounds responsible for odour nuisance in the air and their detection thresholds.

| Name                                | Semi-Structural/<br>Empirical Formula | Odour<br>Threshold [ppb] | Odour<br>Description             | Ref.    |
|-------------------------------------|---------------------------------------|--------------------------|----------------------------------|---------|
| ethanethiol<br>(ethyl mercaptan)    | $C_2H_5SH$<br>$/C_2H_6S$              | 0.011                    | leek, onion                      | [26]    |
| indole                              | $C_8H_7N$                             | 0.0014<br>0.000032       | repulsive, faeces                | [26,27] |
| 1-4 dimethylphenol<br>(p-cresol)    | $C_7H_8O$                             | 0.0018                   | -                                | [26]    |
| pentanoic acid<br>(valeric acid)    | $C_5H_{10}O_2$<br>$/CH_3(CH_2)_3COOH$ | 0.005                    | unpleasant, sweet,<br>honey-like | [26]    |
| skatole                             | $C_9H_9N$                             | 0.006<br>0.000565        | faeces                           | [27]    |
| methanethiol<br>(methyl mercaptan)  | $CH_3SH$<br>$/CH_4S$                  | 0.07<br>0.001            | rotten cabbage                   | [26,27] |
| 2-thiaethane<br>(dimethyl sulphide) | $(CH_3)_2S$<br>$/C_2H_6S$             | 0.21<br>0.004            | rotten vegetables,<br>garlic     | [26,27] |
| hydrogen sulphide                   | $H_2S$                                | 0.47<br>0.018            | rotten eggs                      | [26,27] |
| trimethylamine                      | $(CH_3)_3N$<br>$/C_3H_9N$             | 4<br>1.7                 | fish                             | [26,27] |
| ammonia                             | $NH_3$<br>$/NH_3$                     | 10<br>5.75               | sharp, irritating                | [26,27] |
| sulphur dioxide                     | $SO_2$                                | 10                       | sharp, garlic                    | [26,27] |
| xylene                              | $C_6H_4(CH_3)_2$<br>$/C_8H_{10}$      | 38                       | plastic-like                     | [27]    |
| toluene                             | $C_6H_5CH_3$<br>$/C_7H_8$             | 46                       | fruity, tart,                    | [27]    |
| benzene                             | $C_6H_6$                              | 270                      | paint-thinner                    | [27]    |
| dimethylamine                       | $(CH_3)_2NH$<br>$/C_2H_7N$            | 340                      | fish                             | [27]    |
| methylamine                         | $CH_3NH_2$<br>$/CH_5N$                | 470<br>0.02              | fish                             | [26,27] |
| acetic acid                         | $C_2H_4O_2$<br>$/CH_3COOH$            | 1000                     | vinegar                          | [27]    |

### 3. The Nature of Malodorous Gases in Relation to Their Detection

In order to take appropriate measures to eliminate odorous air pollution, a reliable inventory of the sources of odour emissions must first be carried out, which is often a major challenge for the services [28]. This is due to the fact that the mechanism of human odour detection is still not fully understood [29]. The relationship between the odour of chemical substances and their structure as well as the relationship between the perceived odour and the composition of the gas mixture [30] has also not yet been clarified. These facts make the development of universal, reliable and generally accepted odour detectors difficult or even impossible. Currently, most of the methods used are based on the human sense of smell as the detector for odour-intensive air pollution. Unfortunately, this solution is often criticised and its credibility questioned due to the subjectivity of the human nose and sense of smell,

as well as a number of other objective difficulties [31]. It is therefore necessary to search for, test and optimise alternative techniques for monitoring and measuring malodorous compounds, taking into account the diagnosed limitations of the methods used so far. In the nomenclature of environmental engineering, odours are all substances that have the ability to stimulate the nerve cells of the olfactory epithelium, both those that are generally perceived as unpleasant and those that evoke pleasant experiences [32]. Odour nuisance arises from exposure to compounds that are classified as unpleasant and disturbing odours, but also from constant exposure to compounds that may evoke pleasant sensations or from their excessive concentration [33]. The degree of odour nuisance perceived by humans is mainly determined by the type and concentration of odorous substances, but not only. The intensity, duration and adaptability of the human body are also mentioned [34]. Odour is usually characterised by five basic parameters (CICOP), including C—concentration, I—intensity, C—character, O—offensiveness and P—persistence [35].

Odour persistence means that odours persist over a longer period of time with little change in intensity. The quantitative investigation of the kinetics of changes in odour intensity is difficult and requires the use of appropriate scaling methods. For example, direct assessment of decreasing odour intensity over time requires comparison with a standard. This does not guarantee that the rating scale used in subsequent determinations will be exactly the same (standards also change odour intensity over time). Intensity, character/type of odour and hedonicity are qualitative characteristics of odours. The hedonic quality of the odour, i.e., the determination of the degree of dislike or pleasure in the odour, is usually determined on a scale of one to seven points based on surveys of the population or a team of experts. The odour intensity, i.e., the strength of the odour (weak–strong), is also usually determined on a scale of one to seven points. On the other hand, the character of the odour is assigned to a specific odour group. Different classifications are used depending on the centre carrying out the assessments [36]. To determine the concentration, you can perform analyses by determining the complete chemical composition (qualitative and quantitative) of the tested gas or by determining the value of the odour concentration (expressed, for example, by the number of odour units).

It should be emphasised that a significant analytical problem arises due to the lack of clear correlations between the odour of chemical compounds and their structure and the impossibility of directly and closely linking the odour to the composition of the gas mixture. It is difficult to predict and determine the odour experiences associated with such a mixture on the basis of chemical analysis. Possible interactions between odorants (synergy, masking, neutralisation) mean that the use of a method based on chemical analysis (both qualitative and quantitative) does not guarantee a clear answer to the odour experiences [37,38]. Due to the shortcomings and limitations mentioned above, many people consider techniques based on the determination of odour concentration to be a much better method of gas analysis. These methods are based on sensory analysis. They require a rigorous application of procedures and great discipline in carrying out investigations. Therefore, the key is the conscious choice of method, or sometimes the need to use both at the same time. Below is a comparison of the diagnosed strengths and weaknesses of sensory and analytical methods for assessing the olfactory quality of air (Table 2) and typical measurement ranges and potential sources of errors in the obtained results (Table 3).

**Table 2.** Comparison of methods for measuring odour nuisance in the air.

| Measurement Technique                                | Measurement Type   | Detector Type                                | Disadvantages                                                                                                                                                                                                                                    | Advantages                                                                                                         |
|------------------------------------------------------|--------------------|----------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|
| <b>Methods Based on Classical Chemical Analysis</b>  |                    |                                              |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Chromatographic Analysis                             | Emission/Immission | Chemical/Electro-chemical/Optical, etc.      | Difficulties in interpretation for odorant mixtures (synergy, masking, neutralisation phenomena)<br>Technical challenges due to the detection of very low concentrations<br>High costs due to the necessity of detecting very low concentrations | Facilitates the selection of an appropriate deodorisation method<br>Possibility of high automation of measurements |
| Electrochemical Sensors                              | Emission/Immission | Electrochemical                              |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Optical Sensors                                      | Emission/Immission | Optical                                      |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Mass Sensors                                         | Emission/Immission | Chemical                                     |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Biosensors                                           | Emission/Immission | Biological                                   |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Electronic Nose                                      | Immission          | Chemical/Electro-chemical/Optical/Biological |                                                                                                                                                                                                                                                  |                                                                                                                    |
| <b>Methods Based on the Human Nose as a Detector</b> |                    |                                              |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Dynamic Olfactometry                                 | Emission           | Sensory                                      | Lack of chemical composition knowledge—Difficulty in selecting a deodorisation method<br>Subjectivity in perception—requires strict adherence to procedures<br>The number of personnel required for measurements                                 | Enables the analysis of gas mixtures<br>Methods most closely resembling human sensory experiences                  |
| Field Olfactometry                                   | Immission          | Sensory                                      |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Inspector Team                                       | Immission          | Sensory                                      |                                                                                                                                                                                                                                                  |                                                                                                                    |
| Surveyors                                            | Immission          | Sensory                                      |                                                                                                                                                                                                                                                  |                                                                                                                    |

**Table 3.** Typical measurement ranges and potential sources of errors in the obtained results.

| Measurement Method                                  | Measurement Range                                                                                                                                                                             | Typical Issues and Sources of Errors                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            | Ref.    |
|-----------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|
| <b>Methods based on classical chemical analysis</b> |                                                                                                                                                                                               |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 |         |
| Chromatographic analysis                            | ppt–%                                                                                                                                                                                         | Knowledge of gas composition is required for proper selection of chromatographic column, solvent and operating parameters. Averaging necessary to obtain a representative sample and appropriate sample quantity (signal noise and disturbances). Stable sample dosing required (broad, irregular chromatographic peaks).                                                                                                                                                                                                                       | [39–43] |
| Electrochemical sensors                             | Depends on the type of odorant:<br>H <sub>2</sub> S: 0–1000 ppm<br>NH <sub>3</sub> : 0–1000 ppm<br>Mercaptans: 0–5 ppm<br>VOCs: 0–1000 ppm<br>Selected sensors capable of ppb-level detection | Temperature and humidity affect sensor sensitivity and stability. Exceeding the measurement range causes erroneous readings. Long-term exposure to high concentrations leads to sensor degradation.<br>Cross-sensitivity to other gases causes signal disturbances and misinterpretation. Reaction and recovery time may extend measurement duration.<br>Sensor ageing and wear cause sensitivity decline.<br>Regular calibration required. Membrane damage or contamination may block gas access to the electrode, resulting in false results. | [44–46] |

Table 3. Cont.

| Measurement Method                                   | Measurement Range                                                                | Typical Issues and Sources of Errors                                                                                                                                                                                                                                                                                                                                                           | Ref.       |
|------------------------------------------------------|----------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|
| Optical sensors                                      | 1 ppm–10 ppm                                                                     | Cross-sensitivity to other gases causing signal disturbances and misinterpretation. Temperature, humidity, and pressure affect sensitivity and stability. Limited selectivity—response to groups of compounds. Regular calibration required. Low resolution and sensitivity for certain gases. Optical contamination, dust or moisture deposition on sensor surfaces.                          | [45,47]    |
| Mass sensors                                         | ppt–ppm                                                                          | Possibility of ionic interference and signal overlap. High sensitivity to changes in ionisation conditions. Regular calibration required. Matrix effects—interference from other components causing signal disturbances and misinterpretation. Low resolution may cause difficulties in distinguishing compounds with very similar masses.                                                     | [47,48]    |
| Biosensors                                           | ppt–ppm                                                                          | Limited selectivity—response to groups of compounds. Temperature, humidity and pressure affect sensitivity and stability. Ageing of biological elements. Calibration issues. Cross-sensitivity to other gases causing signal disturbances and misinterpretation.                                                                                                                               | [49–51]    |
| Electronic nose                                      | ppm–%                                                                            | Low selectivity of individual sensors—sensors respond to groups of compounds. Temperature, humidity and pressure affect sensitivity and stability. Sensor ageing and wear cause sensitivity decline. Regular calibration required. Data interpretation limitations—classification model errors may lead to false recognitions. Primarily a classification tool rather than a quantitative one. | [45,52,53] |
| <b>Methods based on the human nose as a detector</b> |                                                                                  |                                                                                                                                                                                                                                                                                                                                                                                                |            |
| Dynamic olfactometry                                 | 10–10 <sup>7</sup> ouE/m <sup>3</sup>                                            | Sensory variability of the panel, dilution precision, environmental conditions, panellist adaptation, sample collection errors.                                                                                                                                                                                                                                                                | [52]       |
| Field olfactometry                                   | 1 to 500 ouE/m <sup>3</sup>                                                      | Subjectivity of sensory assessment. Selection and training of measurement personnel. Atmospheric and environmental conditions. Difficulties in measuring very low or very high concentrations.                                                                                                                                                                                                 | [47,54]    |
| Inspector teams                                      | From the odorant's olfactory detection threshold (approx. 1 ouE/m <sup>3</sup> ) | Determination of “odour hours”. Subjectivity of sensory assessment depending on inspector teams. Selection and qualification of inspectors. Atmospheric and environmental conditions. Equipment limitations where devices are used—accuracy of olfactometric instruments.                                                                                                                      | [47]       |
| Surveys                                              | From the odorant's olfactory detection threshold (approx. 1 ouE/m <sup>3</sup> ) | Qualitative and semi-quantitative (usually based on rating scales). Subjectivity and individual variability. Influence of psychological and environmental factors. Lack of standardised methodology. Issues with sample representativeness.                                                                                                                                                    | [47]       |

To determine the value of the odour concentration, the number of so-called odour units is specified. The number of odour units indicates how often the sample is diluted with an inert gas (without substances that cause odour sensations) until the odour detection threshold is reached. The inert gas is usually clean air or nitrogen. Devices called olfactometers are used for this purpose [55,56]. In a sample containing a type of odorous substance, the odour concentration can be calculated using quantitative chemical analysis based on the following Equation (1), which, however, requires knowledge of the previously determined odour detection threshold.

$$S_{OC(ou/m^3)} = \frac{S_{O(\mu g/m^3)}}{S_{ODT(\mu g/ou)}} \quad (1)$$

where  $S_{OC(ou/m^3)}$ —odour concentration [ $ou/m^3$ ];  $S_{O(\mu g/m^3)}$ —odorant concentration [ $\mu g/m^3$ ] and  $S_{ODT(\mu g/ou)}$ —odour detection threshold [ $\mu g/ou$ ].

Human odour receptors are stimulated by odour-producing substances in certain concentrations. Both too low and too high concentrations can lead to a lack of such experiences. If we only add an odour-intensive compound to odourless air (inert gas), we can determine the lowest concentration at which our body perceives its presence, the so-called odour detection threshold of this compound ( $S_{ODT}(\mu g/m^3)$ ). The odour detection threshold is therefore the minimum concentration of a particular compound that triggers an odour sensation in a certain percentage of the population studied (usually 50% of a representative group of people) [57]. For gases that contain more than one odour-forming compound, the odour detection threshold is determined in a similar way. However, the sum of the detection thresholds of the individual components of the mixture is not equal to the odour detection threshold of the entire mixture (Equation (2)).

$$S_{ODT_{mix\ A,B,C...N}} \neq \sum_{i=A}^{i=N} S_{ODT_i} \quad (2)$$

The odour threshold of a particular mixture should be determined experimentally. The value of the odour concentration is expressed by the so-called odour unit. It is defined as the amount of odorous substance present in one cubic metre of gas that causes the odour threshold to be reached ( $1\ ou/m^3$ —odour unit). In Europe, n-butanol ( $123\ \mu g/m^3 = 0.040\ \mu mol/mol$ ) is usually used as the standard for determining the odour unit in environmental studies. This is indicated in the symbols by the corresponding index— $ou_E$ .

## 4. Classification of Measurement Methods

The techniques for determining the concentration of odorous substances in the air are based on two main groups of methods, namely classic qualitative and quantitative chemical analysis and sensory analysis methodologies.

### 4.1. Chemical Analysis

If the gas contains a type of odorant, chemical analysis often allows a clear correlation between its concentration and the odour sensations using the Weber–Fechner law (Equation (3)) or Stevens' law (Equation (4)) [58,59].

$$I = C \ln \frac{B}{B_0} \quad (3)$$

where  $I$ —odour intensity;  $B$ —odorous substance concentration;  $B_0$ —olfactory detection threshold of the odorous substance and  $C$ —empirical constant characteristic of the odorous substance.

$$I = a \cdot B^n \quad (4)$$

where  $I$ —odour intensity;  $B$ —odorous substance concentration and  $a, n$ —empirical constants characteristic of a particular odorous substance.

On the other hand, it is believed that the chemical analysis of a mixture of different types of odorous substances is theoretically possible but poses too many problems of interpretation to be used on a large scale to determine odour experiences. If the composition of an odorant mixture is determined qualitatively and the concentration of the individual components is specified, it is difficult to predict the intensity of the odour of such a mixture. This is due to olfactory interactions between the gas components, such as synergism, neutralisation or masking of the odour. The intensity of the odour of the mixture usually deviates completely from the predictions made on the basis of the odour thresholds of the individual odorous substances and the values of their concentrations in the tested gas. If the intensity of the odour is higher than expected, we speak of a synergy of odours. The perceptibility of the odour is enhanced by the mutual interaction of two or more gas components with each other. If the odour intensity of the mixture is lower than expected, we speak of a neutralisation (or compensation) of the odour. In such cases, we are dealing with a reduction in the perceptibility of the odour or its disappearance as a result of the mutual interaction of two or more odorous substances. Masking refers to a distinct type of interaction where an unpleasant odour is replaced by a pleasant one. The introduced ingredient blocks the perception of an unpleasant odour in favour of a pleasant odour [58]. Not only the type of compound, but also its concentration influences the interactions. Not only odour-causing compounds can be involved, but also those that potentially do not cause odour sensations (when isolated). Their mechanism is not yet fully known, hence the problem with interpreting the results obtained in this way.

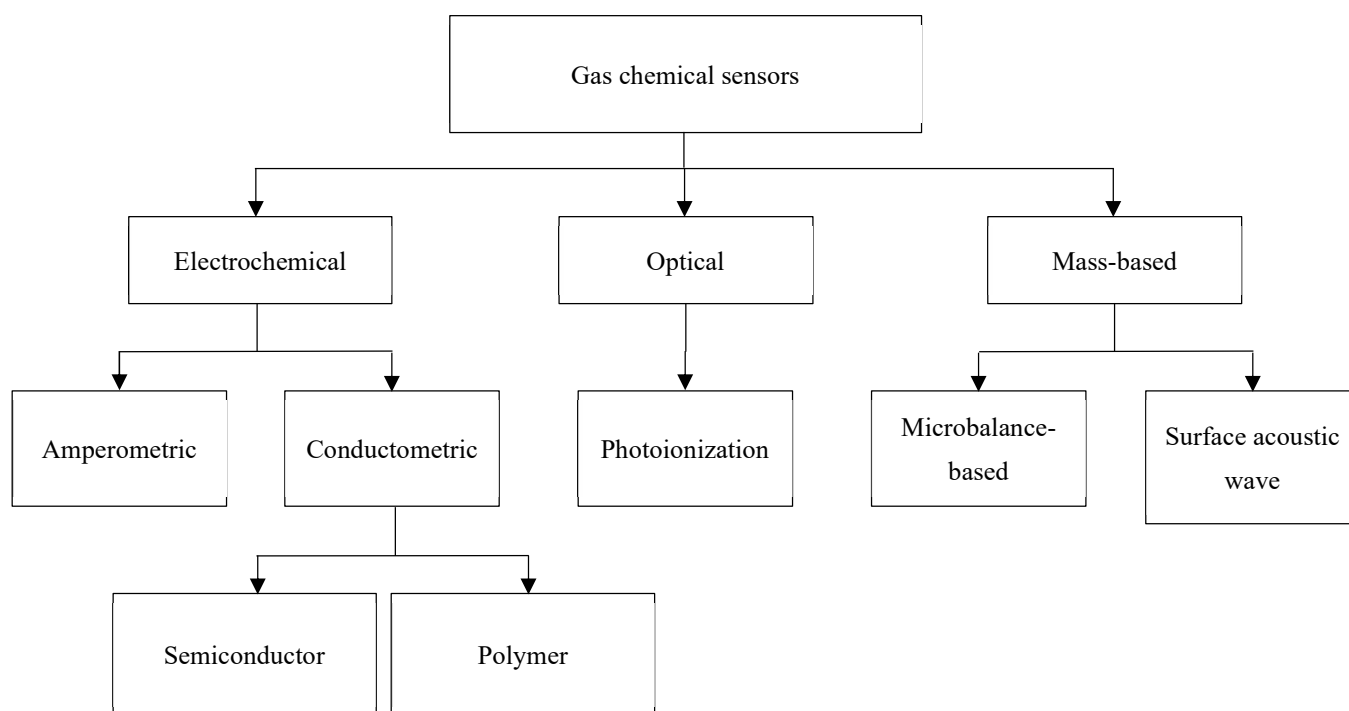
Another problem is the correct determination of the composition of the mixture in terms of quality. It is easy to ignore an important component of such a mixture if its concentration is low (it can be categorised as insignificant background). We do not always have such sensitive research equipment to determine very low concentrations in a gas mixture. It is worth remembering that even very small amounts of an odorant can make a significant contribution to the olfactory experience. This poses a technical problem. In addition, the determination of low concentrations is often associated with higher analysis costs, so that another problem arises—an economic one. However, gas deodorisation requires classical chemical analysis, which requires knowledge of the gas composition. The analysis techniques can be very different. Chromatography with various types of detectors, gas sensors and electronic noses is most commonly used.

Mixture separation techniques, which include chromatography, are used in combination with different types of detectors, e.g., based on spectroscopy, potentiometry, conductometry or polarography. Most commonly used are one-dimensional chromatography techniques, e.g., gas chromatography (GC) in combination with mass spectrometry (MS) or more accurate multidimensional chromatography techniques, e.g., MDGC, also in combination with MS [57,58,60,61]. With these techniques, the composition of the gas can be determined both quantitatively and qualitatively.

To reduce costs, all types of gas sensors with limited selectivity are often used [58,62,63]. They allow data to be collected in real time and significantly reduce the cost of research. These can be specific sensors that target individual odorants, e.g., hydrogen sulphide or ammonia [58], or non-specific sensors that respond to the presence of many compounds from the same group, e.g., conductometric or piezoelectric sensors [31,58,59]. Non-specific

sensors detect the presence of a specific group of chemical compounds in the analysed gas and determine their concentration.

The sensors consist of two basic parts: a receptor part (a chemically sensitive layer with high selectivity for the tested compound or group of chemical compounds) and a transducer part (responsible for generating a signal that can be interpreted). The receptor part is dominated by absorption, adsorption, chemisorption or coordination bonds [64]. The following are examples of a group of chemical sensors used in odourimetric measurements (Figure 1).



**Figure 1.** Chemical sensors used to detect malodorous compounds.

In order to fulfil their task, the sensors for the analysis of odorous substances must be characterised by a low detection limit (close to the detection limit characteristic of the human nose). They should be resistant to the temperature and humidity fluctuations of gases and have good measurement repeatability. Humidity disturbances are an important factor influencing both the sensor resistance and the gas reaction. Water vapour can adsorb competitively on the surface and thus reduce the number of active sites available for adsorption of target molecules (e.g., semiconductor sensors) or interact with the internal electrolyte (electrochemical sensors) [65]. It is also necessary to pay attention to the operating temperature of each sensor. Acoustic surface acoustic wave sensors and polymer sensors are very sensitive to temperature fluctuations, while optical sensors cope well with this problem [66]. In the case of on-site use, the sensors should also be characterised by a short response time and small dimensions. Biosensors are also used. They belong to the group of non-specific sensors. The operating parameters of selected sensors are listed in Table 4 below [64].

**Table 4.** Parameters of selected gas sensors used for the detection of odorous substances [46].

| Sensor Type                 | Operating Temperature | Response Time | Device Lifespan | Signal Stability with Temperature Changes | Signal Stability with Humidity Changes |
|-----------------------------|-----------------------|---------------|-----------------|-------------------------------------------|----------------------------------------|
| Amperometric                | 20–50 °C              | 30–180 s      | Up to 2 years   | Low                                       | Low/Medium                             |
| Semiconductor               | 300–400 °C            | <5 s          | Up to 5 years   | Low                                       | High                                   |
| Polymeric                   | 20–50 °C              | 20–50 s       | Up to 2 years   | High                                      | Low                                    |
| Photoionisation             | 20–50 °C              | <60 s         | Up to 2 years   | Medium                                    | Medium                                 |
| Microgravimetric            | 20–50 °C              | 20–50 s       | Up to 2 years   | Low/Medium                                | High                                   |
| Surface Acoustic Wave (SAW) | 20–50 °C              | 20–50 s       | Up to 2 years   | High                                      | High                                   |

More and more measurement techniques are being developed that are based on a number of different sensors in a single device called an electronic nose [67]. This group of devices also includes those in which chromatographic columns are fitted instead of sensors. The electronic nose is characterised by a fast detection time and the ability to measure several parameters simultaneously [66]. The design of the device is based on the odour receptor cell of the human nose. The device consists of a sampling system, a series of detectors (the so-called sensor matrix) and a system for signal processing and recording. Specialised data analysis techniques, statistical tools and a suitable database of standards are also required to interpret the results obtained with such a device. In an electronic nose system, two essential components must work together synergistically: the sensor array (hardware) and the pattern recognition algorithm (software). Different types of sensors—such as semiconductor, polymer, quartz crystal microbalance or surface acoustic wave sensors—can be used to construct sensor arrays for electronic noses. These sensors can be integrated with both conventional and advanced odour pattern-recognition algorithms. The type of sensors and algorithms used directly affects the sensitivity, selectivity and accuracy of the technology [65]. During analysis, it is crucial to continuously monitor temperature and humidity to prevent sensor degradation [47]. In recent years, there has been a clear trend towards the miniaturisation of sensors, enabling the wide application of electronic noses in environmental monitoring (identification and quantification of odours and volatile organic compounds), in the food industry (quality and safety assessment) and in healthcare (monitoring and diagnosis of diseases using volatile biomarkers) [65].

The pattern recognition algorithm, which is tuned to the sensor array, is a key component of the device that is able to extract valuable information from the captured sensor signals. Pattern recognition methods used in electronic noses include conventional statistical methods such as principal component analysis (PCA), linear discriminant analysis (LDA), support vector machine (SVM) and k-nearest Neighbor (k-NN), as well as more advanced approaches such as artificial neural networks (ANNs), convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [65]. The selection of a suitable algorithm is crucial for ensuring the accurate and efficient performance of the electronic nose in recognising specific gas groups. For simple applications, conventional algorithms such as PCA or LDA are recommended due to their computational efficiency and simple hardware implementation. However, these conventional algorithms face challenges when used in real-world environments with significant noise and interference. For applications such as environmental monitoring, breath analysis in medicine or analysing mixtures of very similar gases, more advanced AI-based algorithms are preferable. Therefore, electronic noses require appropriate preparation—the so-called training. The training consists of introducing standards into the device and creating a corresponding database [68]. The use of the electronic nose is limited to gases with a predictable composition. In order to train

the nose for the odours it is supposed to identify, a series of similar patterns must first be introduced. The training is always geared towards the type of measurement planned [47]. The use of the electronic nose for analysing odorous gases is somewhat limited due to the very low concentrations of VOCs they contain (ppb, ppt level) [65]. The stringent requirements for the detection limits, sensitivity, selectivity and accuracy of the electronic nose may be difficult to fulfil in environmental studies, which is why the human nose is still popularly used as a detector. Table 5 shows the difficulties associated with the standardisation and widespread use of electronic noses as well as the proposed solutions.

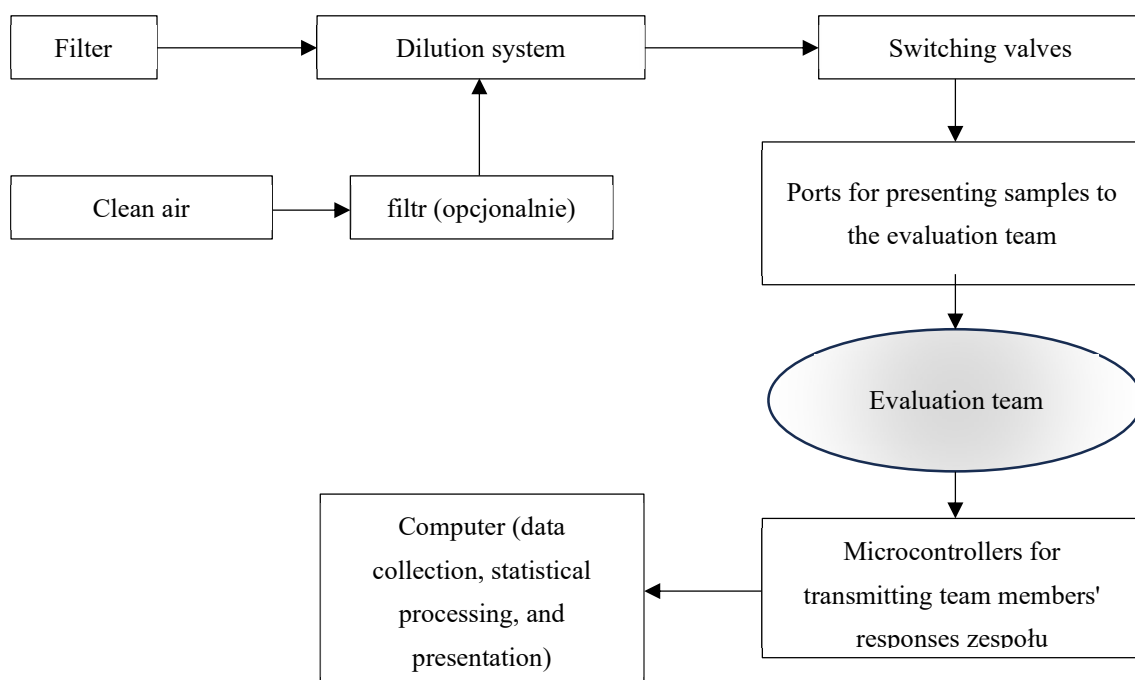
**Table 5.** The main challenges associated with standardisation and the use of electronic noses with the proposed solutions.

| Barriers and Limitations                 | Description                                                                                                               | Solution                                                                          | Ref.    |
|------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|---------|
| Data and Data Labelling                  | An insufficient number of labelled samples and difficulties in correcting data drift affect the performance of AI models. | Transfer learning, semi-supervised learning, advanced drift correction methods.   | [69–71] |
| Sample size and composition              | Differences in the size of training and test sets lead to inconsistent prediction models.                                 | Balanced training sets, cross-validation, context and data distribution analysis. | [72]    |
| Calibration and validation               | Calibration models degrade over time and need to be frequently updated.                                                   | Drift correction, standardisation of calibration, updating the calibration model. | [73]    |
| Feature extraction                       | Extracting representative features from high-dimensional data is difficult.                                               | PCA, deep neural networks, complex signal processing.                             | [74,75] |
| Technical complexity                     | Temperature modulation and selectivity of sensor arrays affect stability.                                                 | Optimisation of temperature control algorithms, sensor architecture selection.    | [76]    |
| Cross-sensitivity and selectivity        | Sensors react to multiple substances, making classification difficult.                                                    | Machine learning for pattern analysis, sensors with lower selectivity.            | [77]    |
| Power consumption and acquisition time   | High power consumption and long measurement times limit on-site use.                                                      | Low power sensors, optimised detection and recovery algorithms.                   | [77]    |
| Noise and outliers                       | The presence of noise and outliers affects classification accuracy.                                                       | Data pre-processing, signal filtering, noise cancellation.                        | [69,72] |
| Evaluation and standardisation           | Lack of consistent assessment methods to replace sensor panels.                                                           | Integrated sensor systems, AI-based validation.                                   | [78]    |
| Reliability of prediction models         | Models degrade over time due to variations in operating conditions.                                                       | Mechanisms for model updating, adaptation to environmental changes.               | [69]    |
| Time required for traditional analyses   | Panel assessments are expensive and prone to human error.                                                                 | Automation of odour assessment, AI-supported systems.                             | [79,80] |
| Overfitting                              | Overfitting makes it difficult for models to generalise to new data.                                                      | Regularisation, feature selection, extension of the data set.                     | [81]    |
| Classification under variable conditions | Sensor drift and environmental changes destabilise the classification.                                                    | Dynamic classification models, stepped classifiers, advanced adaptive algorithms. | [82]    |

#### 4.2. Sensory Analysis

The human nose has far greater capabilities as a detector of odours. Only the human nose can be used to evaluate parameters such as the character or hedonic tone of the odour. Odour evaluation techniques based on the sense of smell can be divided into two groups, the techniques based on subjective organoleptic evaluations and the techniques based on sensory analyses. Sensory analyses must meet high requirements in terms of the repeatability and reproducibility of the results obtained. In principle, they require an objective and quantitative determination of the odour concentration of all odorous substances together. It is therefore possible to use them for the analysis of odour nuisance. Olfactometry is one of the sensory methods. In the literature, a distinction is made between dynamic olfactometry (dynamic dilutions), static olfactometry (static dilutions) and separately classified field olfactometry (in situ studies) [33,62]. It relies on the human nose as a detector, but at the same time ensures the repeatability and reproducibility of the results. Olfactometry is based on procedures for the controlled dilution of samples/flows of odour-intensive gases with an odourless gas. It requires strict adherence to procedures at all stages, starting with the sensory verification, the sensitivity of the evaluation teams, the method of sample collection and presentation, the recording of the results obtained and the application of appropriate statistical methods to develop them. Using this method, we can, for example, determine the odour threshold of a particular compound, the detection threshold or the concentration of odour units in the analysed gas. This allows us to determine the emission and immission values or to model the spread of odorous substances in the field.

The olfactometric method is one of the most technically advanced methods for determining odour concentration. In many European countries, it is based on strict procedures laid down in standards [83]. It uses a device called an olfactometer, which allows an objective determination of the odour concentration in a gas sample using the human nose as a detector [84]. The schematic representation of such a device is shown in Figure 2.



**Figure 2.** Schematic diagram of the measurement of the odour quality of air with an olfactometer.

It is a compact system for odour measurement in the laboratory or under mobile conditions. The device enables the automation and precise control of the sample dilution process and the simultaneous presentation of samples to the evaluation team (usually

four people). It enables precise communication between the team and the computer and automatic statistical evaluation of the data obtained. It enables the immediate presentation of the results. With the help of an odour measurement device (olfactometer), it is also possible to select a representative group of people who can form the evaluation team (panel members) [85]. Table 6 below summarises the most commonly used quantitative methods used by teams of odour specialists in odour assessment. This summary includes approaches that are widely accepted as standard in sensory research and provide an objective and repeatable assessment of odour intensity and quality. These methods are an important element of olfactometric analysis and are widely used both in scientific research and in the technical practise of air quality monitoring.

**Table 6.** Frequently used quantitative methods for odour measurement by teams of olfactory specialists.

| Method                          | Basis of Application                                                          | Outcome                                                | Application                                                                 | Ref.       |
|---------------------------------|-------------------------------------------------------------------------------|--------------------------------------------------------|-----------------------------------------------------------------------------|------------|
| Intensity Scale                 | Panellists rate odour intensity on a numerical scale                          | Numerical value (e.g., 0–5 or 0–9)                     | Assessment of environmental odours, products, odour emission analysis       | [36,86,87] |
| Hedonic Scale (Pleasantness)    | Evaluation of odour along the pleasant–unpleasant axis                        | Scale, e.g., from −5 to +5                             | Olfactory comfort analysis, consumer products                               | [88,89]    |
| Threshold Tests (e.g., 3-AFC)   | Determination of the lowest concentration at which odour is detectable        | Detection threshold (e.g., ouE/m <sup>3</sup> , log C) | Certified laboratories, olfactory sensitivity assessment, normative studies | [90–92]    |
| Descriptive Profiling           | Assignment of qualitative descriptors from a predefined lexicon               | Descriptor frequency pattern                           | Characterisation of complex odours, food and environmental analysis         | [93–95]    |
| Reaction Time/Identification    | Measurement of response time and accuracy of odour identification             | Mean reaction time (s), % of correct responses         | Cognitive research, neurological testing (e.g., Alzheimer’s, Parkinson’s)   | [96,97]    |
| Olfactory Adaptation            | Repeated exposure—evaluation of intensity decreases over time                 | Intensity vs. time curve                               | Assessment of olfactory discomfort during prolonged exposure                | [98–100]   |
| AI/E-nose Assisted Measurements | Prediction of perception based on signals from chemical sensors and AI models | Predicted intensity, threshold, odour classification   | Panel calibration, real-time measurements                                   | [45,52,53] |

#### 4.3. Combined Methods

In recent years, especially in the USA and Europe, techniques have been developed that combine traditional gas chromatography analysis with sensory detection. These methods are considered to be very expensive. Gas chromatography–olfactometry (GC-O) is a method based on the separation of odour components from a complex mixture. Suitably trained personnel then smell the eluate using a specially developed connector connected in parallel to conventional detectors to detect the presence of odour compounds [52]. After separation and elution by the chromatography column, every odour compound that can trigger an odour stimulus can be detected by the evaluation unit via a specially developed detection port. A conventional detector (e.g., a flame ionisation detector (FID) or mass spectrometer (MS)) is connected in parallel to this detection port in order to detect the type

of compound perceived by the evaluation unit. In this way, each compound separated by chromatography can be described in terms of the quality of the perceived odour and its intensity (sensory analysis—assessment team), and also qualitatively and quantitatively identified (chemical analysis—conventional detector). The precision and accuracy of the collected data are ensured by dividing the stream leaving the gas chromatograph (at a constant division coefficient—appropriate flow dividers) and directing the precisely divided streams to two different detection methods [101]. The popular combination with a mass spectrometer as a conventional detector (GC-MS/O) enables not only the evaluation of odour compounds, but also their identification based on information about the mass spectrum. Simultaneous sensory evaluation makes it possible to determine whether a particular compound, separately from the others present in the mixture, is odorously active (at a certain concentration in the sample extract that is above the sensory detection limit) [102]. Assessors may be asked to indicate the time of odour perception (indicating the beginning or the end) and to describe the hedonic tone or intensity, e.g., using an odour intensity scale. Only a portion of the volatiles present in the matrix can really contribute to the overall odour perception and not all odorants contribute equally to the odour profile of the mixture, therefore a large peak area in GC does not necessarily correspond to a high odour intensity [101]. The use of combined techniques facilitates the solution to this problem. The separation of chemical and sensory analysis also encounters the problem of the low sensitivity of the analytical instruments to the human nose. Important odorants may be present in the matrix in trace amounts, and other odorants present in the matrix may complicate the evaluation, e.g., by co-elution (peak overlap) [52]. The simultaneous combination of sensory and analytical techniques therefore enables a more in-depth analysis of the results obtained and can improve accuracy.

The GC-MS/O method is used, for example, to determine the effectiveness of different gas deodorisation systems and to develop a suitable and cost-effective strategy [103,104]. Gas chromatography–mass spectrometry–olfactometry (GC-MS/O) compounds are modifiable, and there are already known combinations of multidimensional gas chromatography with mass spectrometry and olfactometry (MDGC-MS/O). If the composition of the matrix is very complex (the complexity of the matrix leads to multiple peak overlaps), one-dimensional gas chromatography may be inadequate. The principle of multidimensional gas chromatography techniques is based on the use of sequentially connected capillary columns, which are characterised by different selectivity towards the chemical compounds present in the sample mixture. The choice of column combination is closely related to the composition of the matrix and the purpose of the analysis. Usually, the first column (the so-called first dimension) is non-polar and the second (the second dimension) is polar [101], although the “reverse column configuration” is also used [105]. Unseparated sample fractions leaving the first column are transferred to the second column using a device that supports the heartcut or modulation process [106]. MDGC-MS/O are used to analyse complex mixtures of odorous substances and to identify odour-active compounds. This shifts the evaluation of odour emission from purely olfactometric evaluation to the characterisation of the volatile components responsible for the odour nuisance.

MDGC-MS/O has been used to identify odorous substances in livestock farms [107]. However, it should be noted that in combined methods based on chromatographic techniques, volatile compounds are evaluated separately. The aspect of interactions between the odorous substances in the mixture is omitted here. Therefore, an integration of the obtained data with the sensory properties of the whole gas is necessary to understand the olfactometric phenomenon. A similar approach to the problem is proposed by the aforementioned e-noses. E-noses are a promising alternative for monitoring and analysing gases in real time. However, unlike gas chromatography, which separates compounds based on their chemical

properties, e-noses use sensor arrays to recognise compounds through pattern recognition. Here, the individual sensors only react to certain compounds/groups of compounds. Only the signals collected from the individual sensors provide a comprehensive picture of the gas being tested. The combination of sensors in e-noses can improve the accuracy of measurements but requires the optimisation of their operation depending on the application. The first step is to optimise the sensor array—selecting the right sensor types for the gas being analysed [108]. The next step is integration with machine learning [109–111] and combining multiple sensory data to improve the accuracy of odour detection (e.g., combining e-nose data with other sensory stimuli such as machine vision) [112]. Despite advances in the development of these technologies, e-noses face challenges in selectivity and sensitivity, and calibration issues arise in complex odour environments [65].

## 5. Overview of Odour Analytical Measurement Methods

Odourimetric measurements can be categorised into groups based on various criteria. Odour measurements can be carried out on the basis of analyses using equipment, including those described above, on the basis of traditional chemical analyses or sensory analyses and using teams of specially trained and selected experts or on the basis of analyses of survey studies in a given population. If the subdivision criterion is the place where the research is carried out, we can distinguish between laboratory and field studies. In the field, field equipment for conventional chemical analyses (e.g., field chromatographs, electronic noses, sensors) as well as equipment for olfactometric measurements in the field (e.g., field olfactometers) or a team of inspectors working according to procedures based on their own sense of smell (e.g., measurements in a grid or in a stream based on assessment maps, survey analyses) can be used. Laboratory analyses, on the other hand, require samples to be taken and handed over to the laboratory. The location and method of sampling can also be varied. In addition, the measurement can concern both emissions and immissions, similar to other gaseous pollutants.

### 5.1. Emission Measurements

The emission of malodorous gases can be determined, similar to other gaseous pollutants, if the nature of the emission source is known [113]. Emission sources include the following:

- organised (e.g., covered activated sludge chambers in wastewater treatment plants) and unorganised (e.g., stables or landfills);
- active (with forced gas flow, e.g., aerated chambers in wastewater treatment plants or biofilters) and passive (e.g., solid waste landfills, sludge sites);
- point (e.g., chimneys that emit gases), surface area (e.g., sludge areas) and volume (e.g., stables).

The most important aspect in the determination of gas emissions is that the sample taken for analysis is representative. Therefore, samples are taken differently depending on the type of source. We can determine the point emission if we know the concentration of the odorous substances and have data on the volume flow of the emitted gas (Equations (5) and (6)) [114,115].

$$E = S_{OC(ou/m^3)} \cdot V \quad (5)$$

$$E = S_{O(\mu g/m^3)} \cdot V \quad (6)$$

where  $E$ -emission from a point source [ou/s] or [ $\mu g/m^3$ ] and  $V$ -volume flow rate of the emitted gas [ $m^3/s$ ].

Gas samples for the determination of emissions from such sources are taken directly from the emitted stream, e.g., using the so-called “lung method” by averaging the samples collected in a certain time interval. Static or dynamic dilutions can be used for sampling. The measurement of surface emissions is somewhat more difficult. It requires the use of a special chamber for sampling surface emitters. For active source measurements, the air flow rate in the sampling chamber is closely related to the air flow through the active source, while for passive sources the air flow rate is forced by the sampler (typically 0.2–0.3 m/s) [116]. The calculations are based on the knowledge of the operating parameters of the sampler [116], the surface area of the emitter and the odour concentration values (Equations (7) and (8)) [54,114,115].

$$E = \frac{S_{OC(ouE/m^3)} \cdot V_{pr} \cdot P}{P_{pr}} \quad (7)$$

$$E = \frac{S_{O(\mu g/m^3)} \cdot V_{pr} \cdot P}{P_{pr}} \quad (8)$$

where  $E$ —emission of the source  $P$  [ou/s] lub [ $\mu\text{g/s}$ ];  $V_{pr}$ —air flow rate in the sampling chamber [ $\text{m}^3/\text{s}$ ];  $P$ —emitter area [ $\text{m}^2$ ] and  $P_{pr}$ —emitter area under the sampling chamber (in the sampler) [ $\text{m}^2$ ].

Due to the difficulties in determining the air flow through volumetric sources, the measurement of their emissions is the most complicated. In the case of stable buildings, the flow can be estimated by determining the amount of air exchanged in the building per unit of time [117].

## 5.2. Immission Measurements

A fairly common procedure is the measurement of immissions by a team of inspectors in the field, in a “grid” or in a “patch” [116]. The measurements are carried out by a group of inspectors equipped, for example, with field olfactometers, or without equipment (studies based on individual assessment cards—measurement protocols). Various measurement techniques are also used. The measurement results make it possible to characterise the frequency and duration of the selected odour [116]. Before carrying out immission measurements, inspectors are selected on the basis of their odour sensitivity. The team should then be trained in the method of carrying out the measurement and completing measurement reports. To this end, they should also be familiarised with the type of odour that forms the basis for the investigation [116].

Immission measurements can be carried out “in a grid”, i.e., in a planned study area divided into squares. The grid is usually defined on the area of a circle in the centre of which the emission source is located. The area defined in this way is covered with a grid of squares, the corners of which are measurement points. The size of the individual squares depends on the type, height and distance of the emission sources. The disadvantage of the grid measurement method is the duration of the study (at least six months) and the fact that the representativeness of the results depends on the meteorological conditions and the changes in emissions during this period [118].

Measurement “in the plume” is an alternative way of determining the study area. It requires the continuous monitoring of atmospheric equilibrium, wind direction and speed, temperature and other atmospheric factors (e.g., precipitation, fog) [119]. The designated area must be corrected ad hoc if the meteorological conditions change during the investigation. The testers move away from the system in the direction of the wind until they are outside the odour plume. Based on the assumed minimum percentage of odour occurrence, the main and side lines of the odour plume and then the measurement points are determined.

### 5.3. Method for Carrying Out Measurements

As explained above, measurements can be carried out using devices known as field olfactometers or without devices (tests based on individual assessment cards—measurement protocols). The field olfactometer enables the direct measurement of the number of odour units in the air. During the measurement, two air streams are mixed together, one of which is passed through filters (which should be cleaned of odorous substances) and the other is taken directly from the environment. The streams are mixed in precisely defined ratios. By selecting the position of the control valve, the appropriate ratio between the purified air stream (after passing through the filters) and the unpurified air stream (taken directly from the environment) is selected. The inspector gradually increases the proportion of the “uncleaned” air flow until the odour is detected. The number of odour units is determined on the basis of the value of the valve setting in two critical positions (inhalation, when the odour was perceptible, and inhalation, when the odour was not perceptible). Such a measurement is an individual measurement of one of the team members at a given point.

For measurements without an olfactometer, one of the two methods presented below is usually used. In the first method, the air is assessed at intervals over a certain period of time (e.g., according to the recommendations of the German standard VDI 3940, this is an assessment every 10 s over a period of 10 min). The percentage of time during which the odour occurs is determined, i.e., the ratio between the number of “inhalations” during which the odour was perceived and the total number of “inhalations” during the measurement. Another method is to determine the time of odour perception. The percentage of occurrence of the odour is then determined. The ratio of the sum of the individual periods of odour occurrence (time of odour occurrence) to the duration of the entire measurement cycle. This measurement method can be used to determine “odour hours”, for example.

## 6. Surveys

Surveys are often confused with field studies, which are based on measurement maps and conducted by a team of field inspectors (see above). Surveys are conducted with a group of people who are actually from the population being studied. They can be carried out in various ways, namely by analysing complaints from the population, interviewing individuals or randomly selected people in the area under study, regular surveys conducted by a team selected from the inhabitants of the area under study and surveys conducted by telephone.

Surveys are conducted to reliably determine the relationship between odour nuisance and the presence of odour-causing pollutants. They should be conducted by qualified interviewers among a group of people reflecting a given population (e.g., selection of people based on the so-called ordinary random sampling model). It is important to define immission areas (i.e., the total area of possible odour immissions) and control study zones (a zone selected outside the immission area that has a comparable type and arrangement of buildings and remains outside the influence of emissions). The minimum number of surveys must be large enough to be representative of the area. It is important to bear in mind that there may be some surveys with no response (e.g., refusals).

## 7. Modelling Odour Dispersion

Information on emissions, meteorological and topographical data can be used to model the dispersion of odorous substances. Both the spatial and temporal variability in odour concentrations can be simulated. The method of obtaining these data can vary, from estimation to measurement.

There are various approaches to modelling atmospheric dispersion. Three basic types can be distinguished: Gaussian, Lagrangian and Eulerian models. The simplest are the Gaussian models, which assume both the emission plume and the meteorological conditions to be constant over time. The software models AER-MOD, LODM, STING and OdiGauss are based on them [47]. In most cases, they do not take windless and weak wind conditions into account. They are usually used to estimate the average annual and hourly pollutant concentrations. An example of an equation based on the Gaussian model that represents the odour concentration at equilibrium in three spatial dimensions ( $x, y, z$ ) is shown below (Equation (9)):

$$S_{(x,y,z)} = \frac{E}{2\pi\sigma_y\sigma_z u_h} \cdot \exp\left(-\frac{y^2}{2\sigma_y^2}\right) \cdot \left[ \exp\left(-\frac{(z-h)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+h)^2}{2\sigma_z^2}\right) \right] \quad (9)$$

where

$S_{(x,y,z)}$ —odour concentration at a point with coordinates  $x, y, z$  (ou/m<sup>3</sup>);

$E^*$ —odour emission rate (ou/s);

$h$ —emission height (m);

$u_h$ —mean wind speed in the atmospheric layer from  $z = 0$  to  $z = h$ ;

$\sigma_y$ —horizontal dispersion coefficient (y-direction), calculated according to Briggs [120] based on atmospheric stability classes defined by Pasquill [121] and

$\sigma_z$ —vertical dispersion coefficient (z-direction), calculated according to Briggs [122], based on atmospheric stability classes defined by Pasquill [120].

When a Gaussian model is applied to a time series of weather conditions, the results can be viewed as integrated quasi-dynamic representations (e.g., repeating hourly dispersion calculations over a year). Pollutant dispersion in Lagrangian models combines stochastic effects as well as including deterministic factors. Based on the measured or estimated odour emission and the simulation of the spread of particles in the atmosphere according to the Lagrangian dispersion model, the immission value at certain points distant from the emission source is predicted depending on the wind speed and direction [118]. Such models can be used under low-wind conditions [54] and are computationally intensive and resource-intensive [114,121]. In addition, there are hybrid models that include both Lagrangian and Gaussian approaches and are known as puff models (e.g., CALPUFF) [47]. They characterise the dispersion of pollutants using clouds with a constant volume (so-called puffs). The concentration values in these clouds are determined by the Gaussian method, while the paths they follow are determined by the Lagrangian method.

Eulerian models (grid models, 3-D models) are mathematically the most advanced and therefore more accurate. The dispersion calculations are carried out in a three-dimensional area. Eulerian models (e.g., CALGRID, ModOdour) make it possible to calculate the average pollutant concentration at certain receptor points, even for turbulent flows [47,123]. The disadvantage of Eulerian models is the considerable need for computing resources (higher operating costs) [114,123].

Regardless of the model, the necessary input data are topographical and orographic data or meteorological data such as temperature, humidity and air pressure, wind speed and direction, precipitation or solar radiation [47].

Odour emission measurements can be carried out using the dynamic olfactometry method, e.g., according to the EN 13725 standard, the VDI 3880 and VDI 3884-1 guidelines. The disadvantage of the dispersion modelling method is that for some sources, such as diffuse sources or area sources, the emission value is difficult to determine. In addition, the meteorological data are not always representative for a specific location [33].

## 8. Solutions Used Around the World

Possible differences of opinion on the methods used to measure odorous substances lead to difficulties in developing a common approach to odour control policy. In European Union countries, odour is regulated by Directive 2010/75/EU of the European Parliament and of the Council of 24 November 2010 on industrial emissions [124]. It is supported by standards on measurement methods, e.g., for dynamic olfactometry [125] and on-site inspection [126]. It establishes general principles for setting odour limits for many types of industrial activities. The control covers, for example, the energy industry, metal production and processing, waste management, the chemical and mineral processing industries and agriculture (e.g., animal husbandry). Installations in this area of activity may be operated if they have a licence whose conditions are defined in such a way that a high level of protection for the environment as a whole is achieved. They are generally based on the concept of best available techniques (BATs). In order to determine BATs, reference documents for BATs (so-called BAT reference documents) are drawn up [33,127]. The emerging BREFs also contain a new value for the emission levels associated with the best available technology (AEL BAT), which defines a set of emission limit values for each installation applying for a permit [33]. However, the BAT reference documents are neither prescriptive nor exhaustive and do not exempt national authorising authorities from carrying out assessments for specific sectors. In several European countries, there are also other legally binding documents and guidelines on odour. These provisions are most commonly used when detailed criteria are not specified in the BREF or when they are missing.

In France, in addition to the general odour control regulations based on the Industrial Emissions Directive, there are specific odour control regulations for two types of activities: animal by-products processing plants and composting plants. The legislation uses odour concentration values measured according to the EU standard EN 13725 and the frequency of occurrence of odours. The regulations also concern the frequency of measurements [33]. In Austria, there is no law regulating odour nuisance at a national level and odour nuisance is regulated qualitatively (e.g., unacceptable odour is not permitted). The Industrial Emissions Directive only applies to a few types of industrial activities. However, specific odour limit values based on olfactometric tests and modelling apply to some installations that generate odours. For example, in the livestock directives, a certain distance between the installation and areas inhabited by humans (distance) is defined using a dispersion model. It is determined on the basis of emissions from livestock facilities estimated from the number and type of animals, the ventilation system, manure removal or storage and the type of animal feed [128].

Similarly, in Bulgaria, there is no law regulating odour nuisance at national level. Here, only the emissions of certain odorous substances (e.g., hydrogen sulphide) are regulated, without reference to their odour characteristics [128]. In Spain, some municipalities have decided to develop their own odour control regulations (Barcelona, Girona, Alicante, Murcia, Canary Islands). These regulations are usually focussed on a certain type of establishment. Local regulations are also drawn up, e.g., for bars or restaurants. The regulations are based on various aspects [128]:

- odour limits depending on the odour threshold of the substance;
- use of dynamic olfactometry for emission measurements and dispersion modelling,
- changes to urban planning, designation of areas in which a potentially nuisance industrial plant may not be located;
- the establishment of a standardised register of citizen complaints and, on this basis, the limitation of areas in which an industrial installation that may cause odour nuisance can be located;

- mathematical studies that take into account the following: odour concentration, hedonic intensity, odour duration, periodicity, wind direction, etc.;
- the application of a method based on field inspection [126].

In Germany, odour nuisance is regulated by Section 3 (1) of the Federal Immission Control Act [33,128]. Odour pollution in the environment is determined on the basis of the so-called odour hour by recording the odour above the detection threshold and determining its frequency (number of odour hours per year) [128]. The analyses are carried out on the basis of measurements in a grid (standard EN 16841 part 1 [126]) or as a result of dispersion models. In Italy, several regional laws have been published (Lombardy, Trento, Piedmont) whose regulations are based on dynamic olfactometry and dispersion modelling. In Puglia, the situation is slightly different, the criteria are based on the sensitivity of the people within their reach. Sensitivity is categorised into eight different groups: from areas where hospitals are located (restrictive level) to industrial or agricultural areas [128]. Although Directive 2010/75/EU of the European Parliament and of the Council of 24 November 2010 on industrial emissions [124] aims, among other things, to control odour emissions, there is unfortunately no direct implementation of this initiative in the official regulations of most European countries due to analytical problems.

In East Asian countries, there are also regulations for odour emissions in addition to the requirements set at the “receiving point”. In China, there are standards for both organised and non-organised sources. In Japan, there are general national regulations, but also more detailed regulations at the local level. Local authorities have the right to choose one of two regulations: based on odour indicators or odour concentrations [33]. In the United States, the Environmental Protection Agency (EPA) does not regulate odour as a pollutant. Individual states and local jurisdictions have attempted to regulate it. The most common method for regulating odour is field olfactometry. It is used by ten states [33]. Ten US states regulate agricultural odours directly. Thirty-four states have regulations and guidelines to limit emissions, such as: Distance to Emission Point, Manure Management Plan, Permits, Land Application of Fertiliser Regulations, Manure Application Training, etc.

In Canada, there are no regulations for odours from industrial and agricultural facilities. There is also no standard method for assessing odours. The most common approach is to measure the odour source using dispersion models to predict off-site odour concentrations. However, odour can be treated as a pollutant that has an adverse effect and is therefore subject to regulation (e.g.,  $\text{NH}_3$ ,  $\text{H}_2\text{S}$  or other reduced forms of sulphur). There are also a variety of approaches to regulating odour management in Latin American countries. Chile is currently introducing a number of measures based on olfactometric studies to develop regulations for various industries, e.g., pig farms, fisheries and fish processing, wastewater treatment plants, the pulp industry or landfills. Colombia has also started to regulate the method for determining odour concentration using olfactometric methods. A resolution has been drawn up setting limits for odorous substances such as  $\text{H}_2\text{S}$ , reduced sulphur content (TRS) and  $\text{NH}_3$ . The main objective of odour regulation is to promote good environmental practices [33].

In Australia, the law varies by region. In the different states, they are based on different parameters: odour concentration, frequency of occurrence of odours, odour intensity, but also chemical composition. In Western Australia, the focus is on odour intensity, in New South Wales and Victoria, on chemical analysis and odour concentration. Several Australian states use odour assessment criteria based on the population of the location. In New Zealand, sensitivity at a particular location is also based on land use characteristics (time of day; reasons why people are at a particular location) [33].

Different philosophies and different regulatory systems make it difficult to develop a single, common approach to odour policy. However, many regions have adopted ap-

proaches using different quantitative and qualitative methods that are appropriate for setting and enforcing odour regulations in their regions (Table 7).

**Table 7.** Advantages and limitations of selected approaches to legally sanctioned odour assessment methods worldwide.

| Assessment Approach                                                          | Region/Country                                                                                                                                                                                              | Advantages                                                                                                                                                    | Limitations                                                                                                                                                                       | Ref.        |
|------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------|
| Emission-based measurement—odour concentration at the emission source        | Europe: Germany, France, Austria, Belgium, Denmark, UK, Hungary, Italy Asia: Japan, China, South Korea South America: Colombia, Chile North America: USA, Canada Central America: Panama Oceania: Australia | Standardised methodology                                                                                                                                      | Does not account for odour immissions—lacks assessment of population exposure and impacts on adjacent areas. Limited public trust in sensory methods.                             | [57,128]    |
| Emission-based measurement—odour emission factor at the source               | Europe: Germany, UK Asia: Japan North America: Canada                                                                                                                                                       | Applicable to point and area sources (Germany also includes passive sources). Combines odour concentration and perception.                                    | Challenging for diffuse or variable sources. Ignores meteorological conditions and distance. Limited public trust in sensory assessments.                                         | [33]        |
| Emission-based measurement—concentrations of individual odorous compounds    | Europe: Spain, Italy, Denmark North America: USA, Canada South America: Brazil, Colombia Central America: Panama Asia: South Korea, Japan Oceania: Australia, New Zealand                                   | Based on standardised physico-chemical analyses. Allows continuous monitoring. High scientific credibility. Applicable in both field and laboratory settings. | Frequently lacks correlation with human odour perception, especially in gas mixtures. Sensor performance may be affected by environmental factors. Requires frequent calibration. | [57]        |
| Setback distances—odour index at property boundaries                         | Asia: Japan, China South America: Chile Central America: Panama                                                                                                                                             | Harmonised approaches considering population exposure.                                                                                                        | Public scepticism toward sensory methodologies.                                                                                                                                   | [57,128]    |
| Setback distances—concentrations of odorous compounds at property boundaries | Asia: Japan, China North America: Canada                                                                                                                                                                    | Considers human exposure. High reliability. Enables continuous measurements.                                                                                  | Poor correlation with perceived odour. Sensor sensitivity can vary with environmental conditions. Requires regular calibration.                                                   | [57]        |
| Setback distances—dispersion modelling-based separation distances            | Europe: Germany, UK Oceania: Australia, New Zealand                                                                                                                                                         | Predictive capability. Incorporates meteorological and topographic factors. Suitable for planning purposes.                                                   | Often poorly aligned with real-world perception. Methodologically complex. Mostly limited to new installations.                                                                   | [33,57,128] |
| Setback distances—empirical equations                                        | North America: USA, Canada Oceania: Australia, New Zealand                                                                                                                                                  | Computationally simpler than dispersion models.                                                                                                               | Same limitations as above regarding perception. Used primarily for new facilities.                                                                                                | [33]        |
| Exposure assessment—dispersion modelling                                     | Europe: Italy, UK, France, Germany North America: Canada                                                                                                                                                    | Enables quantification of exposure levels. Considers environmental parameters.                                                                                | High methodological complexity. Model variety hinders comparability. Lack of standardisation.                                                                                     | [57]        |
| Exposure assessment—on-site inspections by expert teams                      | Europe: Germany, UK Oceania: Australia, New Zealand                                                                                                                                                         | Standardised protocol. Incorporates real human perception.                                                                                                    | Labour-intensive, time-consuming. Difficult under extreme conditions. Subjective, dependent on panel quality.                                                                     | [129]       |

Table 7. *Cont.*

| Assessment Approach                                                       | Region/Country                                                                        | Advantages                                                                                                         | Limitations                                                                                                                                                                                         | Ref.      |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| Exposure assessment—field olfactometry using portable olfactometers       | North America: USA                                                                    | Less costly and labour-intensive than inspections or modelling. Captures human perception. Increases public trust. | Instantaneous results sensitive to emission dynamics and meteorological conditions. Limited detection range. Technical constraints.                                                                 | [130,131] |
| Exposure assessment—population surveys                                    | South America: Chile                                                                  | Can reflect social perception of nuisance.                                                                         | No standardisation. Requires large sample size. Prone to psychological and contextual biases. Sampling issues.                                                                                      | [57]      |
| Exposure assessment—citizen complaints                                    | Europe: UK North America: USA South America: Colombia Oceania: Australia, New Zealand | Inexpensive and easy to implement.                                                                                 | Data are anecdotal and negative-biased. Results depend on civic engagement. Non-parametric method.                                                                                                  | [57]      |
| Exposure assessment—instrumental odour detection (e.g., electronic noses) | Europe: France, Netherlands North America: Canada                                     | Enables continuous and automated monitoring. Higher trust than sensory panels.                                     | Often misaligned with odour perception. Low sensor specificity. Requires prior knowledge of gas composition. Affected by environmental conditions. Needs calibration. Sensor degradation over time. | [57]      |

## 9. Statistical Methods in Studies on Odour Nuisance

In airborne odour studies, the application of statistical methods is essential for the accurate interpretation of results, the assessment of environmental risks and the support of decision-making processes in odour emission management. The selection of appropriate data analysis techniques not only facilitates the description of basic measurement characteristics, but also enables the modelling of odour phenomena in time and space and the prediction of their occurrence under variable environmental conditions [57]. One of the basic tools used when analysing odour data is descriptive statistics. Arithmetic means, medians, standard deviations, quartiles and percentiles allow a synthetic characterisation of the distribution of odour intensity in a given area or time period [132]. These analyses form the basis for more advanced methods that enable initial detection of data structures, including the identification of outliers and asymmetric distributions typical of environmental datasets. To assess the intensity and frequency of odour occurrences over time, threshold exceedance frequency analysis is commonly used. This method enables the identification of periods of increased odour nuisance, which is particularly important for field monitoring and the validation of emission models [33]. It is often used when setting limit values for odour-emitting installations.

The comparison of measurement results at different locations, under different conditions or before and after the use of odour abatement technologies requires the use of statistical significance tests. In practice, both parametric tests such as *t*-tests and analyses of variance (ANOVA) and non-parametric tests such as the Mann–Whitney U-test or the Kruskal–Wallis test are used, especially if the data do not meet the assumptions of normal distribution. Significance tests allow an objective evaluation of the effectiveness of mitigation measures and the differences in odour perception between different population groups [36]. Regression analysis is an advanced method that makes it possible to model relationships between environmental variables and the extent of odour nuisance. These models can include meteorological factors such as wind speed, temperature and humidity as well as technical parameters of the emission sources [133]. The regression enables the

prediction of the variability of odour intensity and the identification of the most important determinants of odour events.

In the context of analysing time series data, time series analysis techniques play an important role. Methods such as autoregressive integrated moving average (ARIMA) modelling allow the identification of trends, seasonality and anomalies in odour data [134]. This type of analysis is suitable for long-term odour monitoring and the early detection of deviations from the normative emission values. Multivariate analysis, including principal component analysis (PCA) and cluster analysis, enables the reduction in data complexity by identifying patterns and groups within datasets with a large number of variables. These techniques are particularly useful in studies that monitor different emission types or different physico-chemical characteristics associated with odours simultaneously. In studies that require a spatial view of the distribution of odour concentrations, geostatistical methods play an important role. Kriging interpolation and variogram analysis allow the creation of odour distribution maps and the identification of spatial odour-nuisance patterns [135]. These methods also facilitate the integration of measurement results into atmospheric dispersion models.

In recent years, machine learning techniques have become increasingly important in odour research. Algorithms such as random forests, neural networks and support vector machines (SVMs) enable the prediction of odour intensity based on complex input datasets that include meteorological and technical parameters as well as results of subjective odour assessments [136]. Machine learning is particularly effective in modelling non-linear relationships and in the automatic classification of odour emission sources.

Statistical methods for data analysis in odour nuisance research are characterised by high versatility and adaptability to different data types and research objectives. Their appropriate selection and application enable the generation of highly reliable results, which are essential for environmental impact assessments and the development of effective odour mitigation strategies. The statistical methods used for the analysis and interpretation of air quality data related to odour are summarised in Table 8.

**Table 8.** Statistical instruments for measuring odour nuisance.

| Statistical Method             | Description                                                                              | Ref.  |
|--------------------------------|------------------------------------------------------------------------------------------|-------|
| Descriptive statistics         | Data characterisation: mean, median, standard deviation, quartiles.                      | [137] |
| Frequency analysis             | Determination of the frequency of odour threshold exceedances over time.                 | [138] |
| Statistical significance tests | Comparison of data groups (e.g., ANOVA, Student's <i>t</i> -test, non-parametric tests). | [115] |
| Regression models              | Assessment of relationships between environmental variables and odour nuisance.          | [139] |
| Time series analysis           | Identification of trends, seasonality and forecasting of changes.                        | [140] |
| Multivariate analysis          | Data clustering and dimensionality reduction (PCA, cluster analysis).                    | [141] |
| Geostatistical methods         | Analysis of the spatial distribution of odours (kriging, dispersion models).             | [142] |
| Machine learning               | Prediction and classification of odour nuisance (neural networks, random forests).       | [143] |

## 10. Artificial Intelligence in the Measurement of Odour-Intensive Air Quality

Recent advances in artificial intelligence (AI) have significantly enhanced the capabilities of air quality monitoring systems, particularly in the field of odour nuisance assessment. Traditional analytical techniques, although reliable, often prove insufficient when faced with the complexity and variability of odorous emissions. AI offers a transformative approach, enabling the intelligent interpretation of multidimensional sensor data, thereby increasing both the accuracy and responsiveness of air quality monitoring systems related to odour control.

Electronic noses (e-noses), as sensor systems designed to mimic the human sense of smell, constitute one of the primary platforms where AI integration has led to substantial advancements. E-noses utilise arrays of gas sensors to detect a wide range of volatile organic compounds (VOCs) associated with odorous emissions. However, the signals generated by these sensors are often nonlinear, overlapping and sensitive to environmental factors such as humidity and temperature. Machine learning algorithms, particularly support vector machines (SVMs), random forests, and convolutional neural networks (CNNs), are widely used to classify odour types, distinguish between complex gas mixtures, and predict odorant concentrations based on e-nose signals. For example, Wang et al. [144] successfully employed an e-nose system combined with SVM to monitor odorous emissions from a municipal wastewater treatment plant, achieving high classification accuracy across various operational phases and environmental conditions. Their study demonstrated the feasibility of real-time odour monitoring using AI-enhanced e-nose technologies in complex industrial environments. Table 9 contains examples of the use of AI to support the monitoring of odour-intensive objects with an electronic nose and Table 10 provides an overview of the applications of the electronic nose in the analysis of basic environmental gases, taking AI algorithms into account.

**Table 9.** Examples of the use of AI to support the monitoring of odour-intensive objects with an electronic nose.

| Odour Source              | Sensor Type                                                                              | Description                                                                                                                                                                                                                                                     | Ref.  |
|---------------------------|------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|
| Landfill gas odour        | 16 tin oxide sensors (Keeling & Walker)                                                  | The study used artificial neural networks (ANNs), including MLP and RBF models, for quantitative odour prediction (0–200 ou/m <sup>3</sup> ). A strong correlation and very low prediction errors were achieved: MSE 0.000410 (MLP) and 0.000755 (RBF).         | [145] |
| Waste disposal, landfills | 6–8 tin oxide sensors                                                                    | The system used data processing techniques and predictive models to determine odour concentration with an accuracy of 96.4% and a coefficient of $R^2 = 0.90172$ . The analysis included the comparison of the sensory data with the meteorological conditions. | [146] |
| Composting plant          | 6 tin oxide sensors                                                                      | E-nose with supervised data processing and PCA analysis enabled the classification of compost odours and the calibration of emissions up to 1500 ou/m <sup>3</sup> . The system recognised carbon filter breakthroughs in real time.                            | [147] |
| Poultry farm              | 12 sensors (MOS, SnO <sub>2</sub> , WO <sub>3</sub> ) + humidity and temperature sensors | The “Odour Expert” system uses AI to classify farm odours. Field tests on 14 farms showed a high level of agreement with the ratings of the sensory panel ( $R = 0.93$ ).                                                                                       | [148] |

**Table 9.** *Cont.*

| Odour Source             | Sensor Type                                     | Description                                                                                                                                                                                                               | Ref.  |
|--------------------------|-------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|
| Recycling plant          | 6 QMB, 6 MOS, chemical sensors (Jlm Innovation) | The DOSS system is based on multi-sensor signal processing and machine learning. Under field conditions, an $R = 0.93$ and high repeatability and stability were achieved, confirming its effectiveness in odour control. | [149] |
| Waste incineration plant | QCM (AltraSens, Germany)                        | The Odour Vector System used benchmark classification using machine learning algorithms to monitor odours ( $0\text{--}500\text{ ou/m}^3$ ) and evaluate filter efficiency.                                               | [150] |
| Sewage treatment plant   | FOX 3000; 12 MOS                                | The electronic nose proved its usefulness as a warning system for VOC detection. Good repeatability and reproducibility were confirmed (14.8% and 17.6%).                                                                 | [151] |
| Building materials       | KAMINA, 38 sensors on one chip                  | A data model was developed to predict odour intensity based on the correlation of sensory ratings with sensor responses. The variability of humidity was included in further predictive analyses.                         | [152] |

**Table 10.** Overview of the applications of the electronic nose in analysing basic environmental gases with AI algorithms.

| Target Gas                                            | Sensor Type                                                           | Description                                                                                                                                                                                                                      | Ref.  |
|-------------------------------------------------------|-----------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|
| NH <sub>3</sub> , H <sub>2</sub> S and their mixtures | Microsensor array (SnO <sub>2</sub> -CuO, SnO <sub>2</sub> -Pt); WENS | The WENS system with wireless communication used the ARTMAP classifier and the ART-based fuzzy estimator for classification and concentration prediction. 100% classification accuracy and good drift corrections were achieved. | [153] |
| Various volatile organic compounds                    | 14 MOX sensors (Figaro TGS2602)                                       | The data were subjected to regression analysis and PCA, which allowed quantification of trace VOC concentrations (ppb) with low MSE, confirming the effectiveness of AI in prediction.                                           | [154] |
| Acetone, ethanol, butanol, propanol                   | CNT-TiO <sub>2</sub> hybrid nanostructures                            | Classification with PCA and SVM achieved an accuracy of 97.5%. The system worked effectively at room temperature and provided fast and cost-effective VOC detection.                                                             | [155] |
| Formaldehyde, ethanol, acetone                        | TiO <sub>2</sub> nanofibres with PEDOT:PSS, PSS, PPy                  | Impedance analysis and PCA showed a high discrimination capability (variance 97.93%), confirming the use of data analysis algorithms for gas detection.                                                                          | [156] |
| Acetone, chloroform, methanol                         | QCM sensors (NDK Ltd.)                                                | PCA enabled effective discrimination of gases and their mixtures. However, the significant influence of humidity shows the need for further correction of the signals under variable conditions.                                 | [157] |
| H <sub>2</sub> S, NO <sub>2</sub>                     | 6 TGS sensors (Figaro)                                                | Discriminant analysis was used to distinguish gases. The accuracy was dependent on the presence of CO <sub>2</sub> and humidity.                                                                                                 | [158] |
| Chemicals in the air                                  | Mobile robots with gas sensors                                        | The report covers strategies for mapping, tracking and localising odour sources. The importance of developing data processing algorithms and multimodal integration is emphasised.                                               | [159] |

Metal oxide semiconductor (MOS) sensors, extensively used due to their high sensitivity and low cost, play a crucial role in odour-monitoring applications. However, MOS sensors are prone to cross-sensitivity and signal drift over time, which has traditionally

limited their utility in precise environmental measurements. AI-based techniques such as principal component analysis (PCA) for dimensionality reduction, combined with supervised learning models like artificial neural networks (ANNs) and gradient boosting machines (GBMs), have been effectively applied to calibrate and compensate for these limitations. In a study conducted by Moshayedi et al. [160], it was shown that the application of an e-nose based on MOS sensors combined with ANN algorithms allowed for the differentiation of odorous emissions originating from various waste management processes. These results suggest that proper data processing using AI can significantly reduce signal drift effects and improve the reliability of MOS sensor networks in long-term monitoring campaigns.

Photo-ionisation detectors (PIDs), known for their high sensitivity in detecting VOCs, are increasingly being integrated into intelligent odour monitoring systems. Although PIDs provide valuable information on the total concentration of ionisable compounds, they inherently lack the selectivity to identify specific odorous compounds. In this context, AI-driven data fusion methods, including ensemble learning and deep learning architectures, are employed to integrate PID signals with data from additional sensors, such as temperature and humidity sensors. Zhang and Yuan [161] described the application of a PID-based system supported by recurrent neural networks (RNN) to predict odour peaks in the vicinity of petrochemical facilities. Their approach enabled early detection of potential odour complaints, demonstrating the added value of AI in enhancing the specificity and predictive power of PID-based monitoring systems.

In addition to gas-phase sensors, particulate matter (PM) sensors have also found applications in odour air quality monitoring, particularly in industrial and agricultural environments where odorous emissions are often associated with particulate releases. Low-cost PM sensors, which typically estimate particle concentrations based on light scattering principles, can be significantly improved through AI-based signal processing techniques. Kim et al. [162] developed a predictive model based on long short-term memory (LSTM) networks that successfully identified particulate-bound odour events from livestock operations using PM sensor data. Their work demonstrated that AI can effectively distinguish odour episodes associated with particulate emissions from background environmental variability, thus expanding the functional capabilities of PM sensors within odour monitoring frameworks.

Beyond individual sensor technologies, artificial intelligence plays a pivotal role in the optimisation of entire odour monitoring networks. Reinforcement learning algorithms are increasingly being explored to dynamically adapt sensor deployment, optimise sampling strategies, and predict spatial patterns of odour dispersion in real time. Coupling machine learning models with atmospheric dispersion models such as AERMOD and WRF-Chem further enhances the predictive capabilities of odour management systems, enabling early warning and rapid response to odour events. A notable example is the work of Bayraktar and Mutlu [163], where machine learning models were integrated with dispersion simulations to optimise odour mitigation strategies in large industrial complexes.

Overall, the application of artificial intelligence across diverse sensing technologies—including electronic noses, MOS sensors, PID detectors, and PM sensors—represents a breakthrough in the field of odour air quality assessment. AI enables not only improved measurement accuracy and resilience but also the extraction of valuable insights from complex, high-dimensional environmental datasets. As sensor technologies continue to advance and computational power becomes increasingly accessible, the integration of AI-based analytics will undoubtedly remain central to the evolution of intelligent, real-time odour monitoring systems in the coming years.

In recent years, the development of AI-based tools, including quantitative structure–property/activity relationship (QSPR/QSAR) methods, has significantly improved the prediction of odour thresholds for a variety of organic compounds. An example of such an approach is the Monte Carlo method implemented in the CORAL software (CORAL, 2016), which allows the identification of structural promoters for increased or decreased odour sensitivity of molecules based on their SMILES representations [164]. These models show a high predictive value ( $r^2$  up to 0.686 for the validation set) and fulfil the OECD guidelines for the validation of QSAR models. The use of such algorithms can significantly support environmental risk assessment and decision making related to the management of odour emissions, especially in urban environments and near industrial sources.

In recent years, methods for analysing functional brain networks activated by olfactory stimuli, including neutral odours, social odours (e.g., human body odours) and clean air, have developed rapidly. Studies using fMRI in combination with graph theory and methods of statistical analysis of the topology of neural networks have shown that different types of olfactory stimuli activate different brain circuits, allowing for the effective classification and evaluation of these stimuli. An important discovery was the identification of areas such as the fusiform face area (FFA) and the medial orbitofrontal cortex (mpOFC) as nodes in networks activated by chemo-signalling. In particular, the FFA, although classically associated with the processing of visual information, has shown strong involvement in the response to social odours, supporting the hypothesis that the brain interprets these stimuli as social signals [165]. The use of advanced network analysis techniques such as modularity, global efficiency and centrality coefficients enables an objective assessment of the complex olfactory responses in addition to classical sensory methods. This approach is an important step towards the development of AI-supported systems for odour evaluation, which could be used both in environmental research and in neurosensory medicine [165].

## 11. Development Trends and Summary

Odour nuisance has become an increasingly critical issue in environmental protection, especially in the context of expanding urbanisation, industrial intensification and growing public awareness of air quality. Despite significant advances in monitoring technologies and a general improvement in environmental legislation, the management of odour emissions remains a major challenge due to the complex nature of odorous compounds, their variability in time and space and the subjective perception of odours by humans. Current research trends point to three main directions that are pivotal to improving odour nuisance assessment and control: the development of advanced measurement technologies, the harmonisation of legal frameworks, and the implementation of sophisticated data analysis and modelling methods.

Measurement techniques for odour assessment are traditionally classified into subjective and instrumental methods. Dynamic olfactometry, standardised under EN 13725, remains the primary reference method in Europe. It relies on human panellists to determine odour concentration, providing results that reflect actual human perception. However, its limitations, including high costs, dependence on individual variability, and the inability to conduct continuous monitoring, have driven the search for alternative approaches. Among these, electronic noses (e-noses) have gained attention; these devices combine arrays of gas sensors with pattern recognition algorithms to detect changes in air quality. Despite technological progress, their application is still limited by calibration challenges, environmental variability and the complexity of ambient odour mixtures. More advanced instrumental techniques such as selected ion flow tube mass spectrometry (SIFT-MS) and proton transfer reaction mass spectrometry (PTR-MS) allow the real-time, sensitive detection of volatile organic compounds (VOCs) responsible for odours. Additionally, Fourier-transform in-

frared spectroscopy (FTIR) offers the capability to analyse multi-component gas mixtures continuously, making it a valuable complement to traditional methods.

From a regulatory perspective, significant disparities exist globally. Within the European Union, no overarching directive governs odour emissions, leading to heterogeneous national approaches. Germany's GIRL guidelines and the Netherlands' odour unit standards represent advanced regulatory models that establish quantitative emission limits and odour impact criteria. In contrast, many countries, including Poland, lack specific regulations, complicating odour management. In the United States, ASTM E679-19 provides a technical standard for determining odour detection thresholds, while individual states such as Colorado and Minnesota have adopted specific regulatory frameworks addressing agricultural and industrial odour sources. Australia has developed rigorous requirements for dispersion modelling and health risk assessment of odour emissions. Meanwhile, Asian countries like Japan and South Korea have introduced sector-specific odour emission standards. Efforts at the European level, particularly within the framework of the Zero Pollution Action Plan, aim to establish harmonised odour management standards by 2030, which would represent a significant advancement in ensuring equal protection against odour nuisance across member states.

Advances in statistical data analysis have played a pivotal role in modern odour research. Beyond basic descriptive statistics and exceedance frequency analysis, sophisticated techniques such as multiple regression models, logistic regression, and time series forecasting (e.g., ARIMA and SARIMA models) are increasingly used to analyse the relationship between meteorological variables and perceived odour intensity. Dispersion modelling using systems like AERMOD, CALPUFF and WRF-Chem enables the simulation of the transport and spread of odours in the atmosphere, considering meteorological variability, topography and source emission characteristics. Integration of these models with sensory and instrumental data has led to more accurate and comprehensive assessments of odour impacts, as demonstrated in projects such as predicting odour impact with modelling and assessment (PRIMA), which combines dynamic olfactometry, chemical analysis and dispersion simulations.

The rise in artificial intelligence and machine learning has opened new horizons for odour management. Techniques such as random forests, support vector machines (SVMs) and neural networks have been employed to predict odour episode occurrence, classify emission sources, and analyse large, complex environmental datasets. Citizen science initiatives, exemplified by the OdourCollect project in Spain and Smell Pittsburgh in the United States, demonstrate the potential of integrating public odour observations via mobile applications with machine learning models to dynamically monitor and manage odour nuisances. Such initiatives not only enhance the spatial and temporal resolution of odour data but also foster greater community engagement and responsiveness in environmental governance.

The practical implementations of integrated odour management systems further highlight the feasibility and benefits of multidisciplinary approaches. In Rotterdam, a comprehensive odour monitoring network combining instrumental measurements, dynamic olfactometry and meteorological data has been deployed in the port area to manage industrial odour emissions effectively. In Victoria, Australia, stringent regulations require the incorporation of odour dispersion modelling and community impact assessments for new industrial developments. In California's San Joaquin Valley, machine learning models fed with citizen-reported data have been integrated into environmental complaint management systems, allowing the real-time identification of odour events and proactive mitigation measures.

Overall, the future of odour nuisance management lies in the convergence of technological innovation, regulatory harmonisation and community-driven data collection. The integration of real-time monitoring technologies, advanced analytical models and participatory approaches offers a promising pathway toward more effective odour impact mitigation. Achieving sustainable solutions will require not only technical and scientific advancements but also interdisciplinary collaboration across environmental engineering, public health, urban planning and policy-making domains. As awareness of the health and quality-of-life impacts of odour nuisance continues to grow, the development of robust, harmonised and transparent odour management frameworks will become increasingly critical for ensuring environmental justice and public well-being.

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