A systematic bibliometric analysis of studies dealing with fuel-related e-nose applications

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Abstract

Purpose – This study aims to describe a bibliometric analysis of recent articles addressing the applications of e- noses with particular emphasis on those dealing with fuel-related products. Documents covering the general area of e-nose research and published between 1975 and 2021 were retrieved from the Web of Science database, and peer-reviewed articles were selected and appraised according to specific descriptors and criteria.

Design/methodology/approach – Analyses were performed by mapping the knowledge domain using the software tools VOSviewer and RStudio. It was possible to identify the countries, research organizations, authors and disciplines that were most prolific in the area, together with the most cited articles and the most frequent keywords. A total of 3,921 articles published in peer-reviewed journals were initially retrieved but only 47 (1.19%) described fuel-related e-nose applications with original articles published in indexed journals. However, this number was reduced to 38 (0.96%) articles strictly related to the target subject.

Findings – Rigorous appraisal of these documents yielded 22 articles that could be classified into two groups, those aimed at predicting the values of key parameters and those dealing with the discrimination of samples. Most of these 22 selected articles (68.2%) were published between 2017 and 2021, but little evidence was apparent of international collaboration between researchers and institutions currently working on this topic. The strategy of switching energy systems away from fossil fuels towards low-carbon renewable technologies that has been adopted by many countries will generate substantial research opportunities in the prediction, discrimination and quantification of volatiles in biofuels using e-nose.

Research limitations/implications – It is important to highlight that the greatest difficulty in using the e-nose is the interpretation of the data generated by the equipment; most studies have so far used the maximum value of the electrical resistance signal of each e-nose sensor as the only data provided by this sensor; however, from 2019 onwards, some works began to consider the entire electrical resistance curve as a data source, extracting more information from it.

Originality/value – This study opens a new and promising way for the effective use of e-nose as a fuel analysis instrument, as low-cost sensors can be developed for use with the new data analysis methodology, enabling the production of portable, cheaper and more reliable equipment.

Keywords Bibliometrics, Electronic nose, Biofuels, Modeling, Quantitative analysis, Adulteration

Paper type Research paper

1. Introduction

Fossil fuels have served as primary sources of energy for more than a century, but in the past 50 years the oil and gas industry have faced stiff challenges caused mainly by wild variations in the quantity and price of the crude feedstock (Ederington *et al.*, 2019). As a consequence, many countries have been forced to diversify their energy matrix (Doğu and Varişli, 2007; Gao *et al.*, 2018) to find more sustainable solutions involving the use, for example, of ethanol, biodiesel and vehicular natural gas along with mixtures of biofuels and traditional fossil fuels (El-Seesy *et al.*, 2017; Karkanis *et al.*, 2003). One outcome of fuel diversification is the need to establish methods that can be applied in the qualitative and quantitative analysis of the various fuel mixtures to characterize the products and identify adulterants (Chowdhury *et al.*, 2021; Kumar and Pillai, 2020). Although most modern chromatographic and spectroscopic methods, such as gas chromatography (Sudol *et al.*,

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2020), high performance liquid chromatography (Jennerwein *et al.*, 2017), mass spectrometry (Berrier *et al.*, 2020), Fourier-transform infrared spectroscopy (Riley *et al.*, 2016) and nuclear magnetic resonance spectroscopy (Ure *et al.*, 2019), are robust and accurate, they require expensive instrumentation that is not normally available in small laboratories.

Artificial olfactory sensors (electronic noses or e-noses) were initially developed for military purposes, notably for the detection of explosives (Yinon, 2003), but were soon applied in many other fields including, for example, industrial security and food safety (Baldwin *et al.*, 2011; Deshmukh *et al.*, 2015), environmental monitoring (Butt *et al.*, 2022; Capelli *et al.*, 2014; John *et al.*, 2021; Santos *et al.*, 2022) and medical diagnosis (Farraia *et al.*, 2019; Uemura *et al.*, 2021; Wojnowski *et al.*, 2019). They are generally based on conductive polymer sensors or metal oxides that have the property of having the electrical resistance changed when exposed to different volatile substances. With a set of different sensors, one can generate what is called the olfactory profile (formed by different electrical resistance curves over time) of the substrate under analysis and interpret it using different mathematical and statistical methods. Diverse applications of this technology have resulted from close collaboration between researchers and institutions, not only in the development of new sensors but also of novel methods of evaluating the data generated by the devices. The use of e-nose in the analysis of fuels/biofuels as an alternative to traditional methods is, however, more recent and has not yet been consolidated into a worldwide cooperative network.

Despite the considerable literature on the application of e-nose to fuel analysis, examples of collaboration are few and mainly relate to local scientific or commercial interests. Most published studies have focused on the discrimination of groups of samples and/or on the prediction of values of some key fuel parameter, but the numbers of samples analyzed in these experiments have often been insufficient to allow generalizations about the use of e-noses as universal alternatives to more sophisticated and expensive procedures (Kumar *et al.*, 2020; Sampson *et al.*, 2017; Wu *et al.*, 2020). In this context, a novel approach described recently by Siqueira *et al.* (2018), in which the olfactory profiles generated by e-noses were analyzed using a stochastic method, has been shown promising. In this technique, five parameters of olfactive profile are estimated, while usual techniques estimate a single parameter. Therefore, this approach can extract from olfactive profiles more information than other methods and, hence, has proven to be efficient in the qualitative and quantitative analysis of data generated by a small number of sensors and samples. For instance, in Siqueira *et al.* (2018), this technique was compared with other usual techniques of olfactive profile data analysis for classification of different origins of waste cooking oil. While the maximum percentage of samples correctly classified by usual techniques was of 67%, the stochastic method correctly classified 91.6% of samples and, for that, used only the olfactive profiles from three sensors. Moreover, in Vidigal *et al.* (2021), a prediction model for oxidative stability from olfactive profile data was proposed and, through a combination of usual techniques and data from 32 sensors, obtained a prediction quality close to 42%, while, by combination of one of those usual techniques and the stochastic method, the prediction quality doubled (84%), with the use of data from only 11 sensors.

In light of the above, we have performed a systematic bibliometric analysis of articles published between 1975 and 2021 and covering e-nose applications in general, and those related to fuel analysis in particular, with the aim of assessing the state-of-art in data collection and analysis and establishing possibilities for improving international collaboration in the field. Based on this analysis, we have been able to identify the countries, research organizations, source journals, disciplines and authors that are most prolific in the area, the main gaps and research opportunities in the field and the possibilities for international collaboration in the future. The ultimate goal of our study is to assess the use of electronic noses in quantitative and qualitative fuel analyses. For instance, to discriminate groups of samples and/or to predict values of some key fuel parameters. This equipment is easy to be transported, relatively low cost and of great applicable potential. Based on this assessment, it is expected the finding of gaps and identifying of perspectives and trends on this research area.

2. Methodology

Bibliometric analyses are important for mapping the evolution of a scientific field via literature databases and in identifying the most relevant and contextualized studies that could provide answers to specific research questions (Birkle *et al.*, 2020; van Eck and Waltman, 2014; Subramanyam, 1983). It is a transparent, reproducible and reliable process that involves a rigorous literature search based on previously defined descriptors, and is firmly established as an important facet of research evaluation (Oliveira *et al.*, 2019).

The systematic bibliometric analysis described herein was performed in five steps and involved a search of the Web of Science (WoS; Clarivate Analytics, London, UK). According to Birkle *et al.* (2020), the use of WoS has grown and evolved over more than 50 years, a long- and well-established network of partners enables the Institute for Scientific Information to continue to work closely with bibliometric groups around the world to the benefit of both the community and the services that the company provides to researchers and analysts. It was performed by the extraction, selection and appraisal of all relevant studies. Step 1 involved the identification of all records associated with the general topic "e-nose" published during the period of December 1975 to September 2021. Boolean OR operators were used to combine the general descriptors "e-nose" or "electronic nose" or "electronic noses" or "e-noses" or "artificial olfactory sensor" or "artificial olfactory sensors" or "artificial nose" or "artificial noses" or "machine olfaction" or "machines olfaction" in the Title, Abstract and Keyword fields within the WoS Core Collection. The search resulted in 6,005 documents (Table 1), including mainly peer-reviewed articles, papers from proceedings, reviews and meeting abstracts. Step 2 aimed at narrowing down the number of studies to include only articles published in peer-reviewed journals, and this procedure yielded 3,921 documents. Step 3 involved the extraction of articles covering fuel-related e-nose applications, and this was achieved by combining the specific descriptors "fuel", "fuels", "gasoline", "diesel", "biodiesel", "biofuel", "biofuels", "combustible", "combustibles", "biocombustible" and "biocombustibles" using the OR operator resulting in the retrieval of 47 articles. Step 4 entailed an evaluation of the titles and abstracts of these 47 remaining papers to identify those that were strictly within the scope of this

Table 1 Numbers and types of documents from Steps 1 and 2 retrieved from the web of science covering the general topic of e-nose research

Type of document	No.
Articles in peer-reviewed journals	3,921
Papers from proceedings	1,791
Reviews	351
Meeting abstracts	205
News items	42
Editorials	41
Early access	34
Corrections	18
Letters	11
Data papers	10
Book chapters	7
Notes	2
Literary criticism	1
Reprints	1
Retracted publications	1
Total of documents	6,005

review, a procedure that resulted in the exclusion of a further 9 articles. In the final Step 5, the 38 subject-focused articles were assessed in detail to determine the suitability of the contents and filtered to include only those that had been published within the past 10 years. This final evaluation yielded 22 articles, which were analyzed thoroughly and classified into two groups according to their objectives, namely, the prediction of numerical values or the discrimination of samples. The PRISMA flow diagram shown in Figure 1 summarizes the search, extraction, filtration and selection process as outlined above (Hutton *et al.*, 2015).

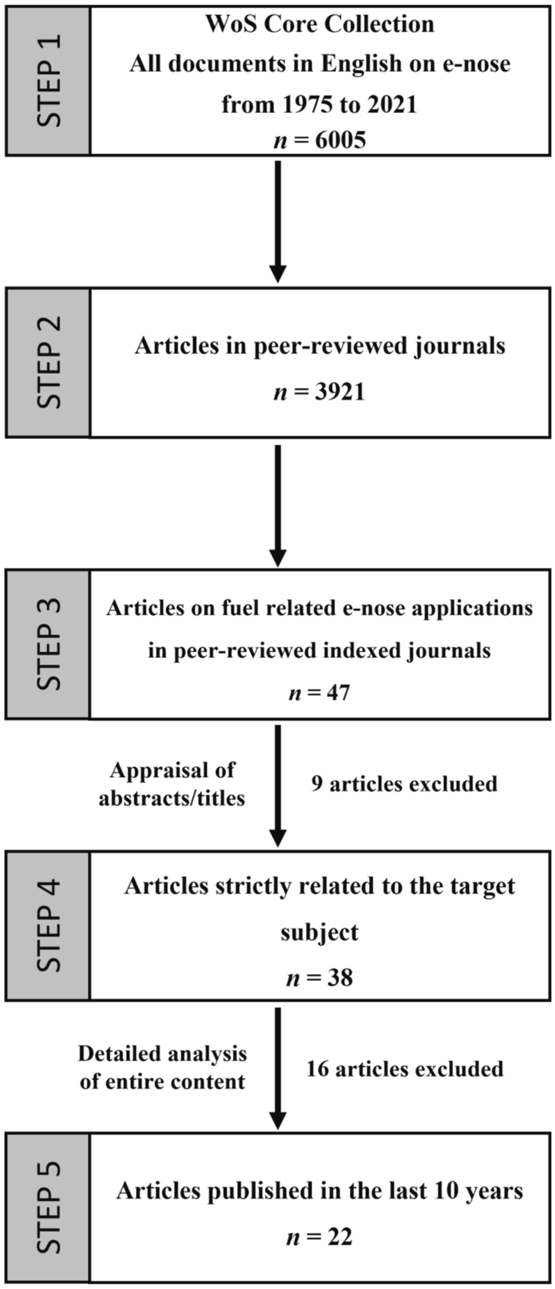
Data concerning producing countries, research organizations and authors, along with source journals, disciplines, cited papers and keywords, were tabulated or presented in the form of knowledge domain maps visualized using VOSviewer (van Eck and Waltman, 2010, 2020) and RStudio (RStudio Team, 2020; Verzani, 2011). To perform descriptive analyses of the bibliographic data, the Bibliometrix package incorporated within the RStudio tool was used.

3. Results and discussion

3.1 Overall analysis of the literature search

The systematic and bibliometric analysis covered the literature summarized in the WoS database relating to e-nose studies in general during the timeframe 1975–2021, and to the application of e-nose to fuel-related products in particular over the past 10 years. The general search retrieved 6,005 documents produced by 13,880 authors and 3,378 research organizations distributed over 106 countries and indexed according to 10,506 keywords. However, only 47 (0.78%) of the total number of documents retrieved from the WoS database were associated with articles fuel-related e-nose applications. Moreover, when only articles strictly related to the target subject published in science citation index expanded (SCIE)-listed journals were taken into account, the proportion of total papers focusing on fuel-related e-nose applications was reduced to 38 (0.63%), showing that this research topic is still in its embryonic stages.

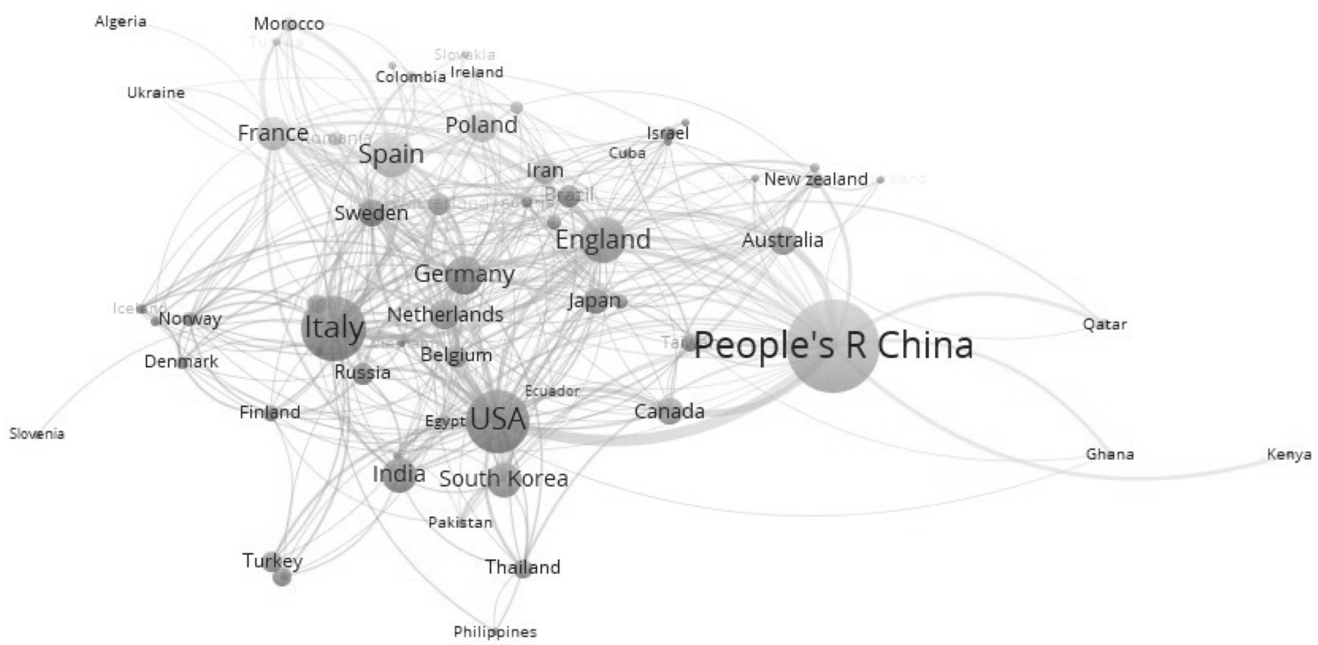
Figure 1 PRISMA flow diagram of the bibliometric analysis showing step-by-step filtering of documents retrieved from the Web of Science



3.2 Quantitative analysis of the search performed using general e-nose descriptors (Steps 1 and 2)

Based on the articles retrieved from Steps 1 and 2 of the bibliometric analysis, it was possible to identify the most prolific countries, research organizations and authors, together with the most common source journals, disciplines, cited articles and keywords associated with e-nose research regardless of the field of knowledge. The knowledge domain map (visualized with VOSviewer) presented in Figure 2 shows each country as a nodal disc, the size of which signifies the relative activity of the country in e-nose research, while the links between nodes represent collaborative ties between the countries in this subject

Figure 2 Knowledge domain map visualized using VOSviewer of the contributions of countries to the general area of e-nose research



area with stronger ties represented by thicker links. The leading countries in the general area of e-nose research with respective documents and citations were China (1043; 15933), Italy (503; 16062), EUA (480; 17443), England (255; 9741) and Spain (242; 7001), while collaborating countries showed a tendency to cluster together in some distinct groups (highlighted in colors such as pink, green, purple and yellow).

The individual organizations with the largest output of publications in the general area of e-nose research were located in Italy, China, the UK, Spain and The Netherlands (Table 2). The Consiglio Nazionale delle Ricerche and the University of Rome Tor Vergata in Italy, along with Zhejiang University in China, were the leading institutions in terms of publications with at least 100 peer-reviewed articles each. The knowledge domain map displayed in Figure 3 shows the contributions of the most important research organizations to e-nose research, with the size of the corresponding nodal disc signifying productivity and links between the nodes indicating collaboration between institutions.

The 10 most prolific authors in e-nose research are listed in Table 3 along with their research output indices and countries of affiliation. As expected, these authors were associated with countries showing the highest productivity in the general area (Table 2). It is important to stress, however, that evaluation of the research performance of an author should take into account other factors in addition to the number of articles published. In this context, Table 3 lists the *h*-index for each author, such value being assigned if *h* of the author's N papers have at least *h* citations each while the remaining (N- *h*) papers have fewer than *h* citations each. In the present case, although the Chinese author J. Wang was the most prolific (88 papers), the Italian authors C. Di Natale, A. D'Amico and R. Paolesse (74, 57 and 52 papers, respectively) each exhibited a greater academic footprint according to their respective *h*-indices. The

Table 2 Top 10 organizations ranked according to their output in the general field of e-nose research

Rank	Organization	Country	Ps	P	*h*	TC	CA	AC	CPP
1	Consiglio Nazionale delle Ricerche (CNR)	Italy	143	3.647	39	4,955	34.65	3,770	26.36
2	Zhejiang University	China	142	3.622	38	3,844	27.07	2,493	17.56
3	University of Rome Tor Vergata	Italy	88	2.244	41	4,680	53.18	3,147	35.76
4	University of Warwick	UK	84	2.142	34	4,361	51.92	3,095	36.85
5	Chongqing University	China	77	1.964	23	1,489	19.34	869	11.29
6	Jiangnan University	China	73	1.862	18	1,030	14.11	880	12.05
7	University of Milan	Italy	66	1.683	23	1,918	29.06	1,556	23.58
8	University of Amsterdam	The Netherlands	57	1.454	27	2,325	40.79	1,217	21.35
9	Consejo Superior de Investigaciones Cientificas (CSIC)	Spain	55	1.403	30	2,157	39.22	1,588	28.87
10	Nanjing Agricultural University	China	51	1.301	15	823	16.14	703	13.78

Notes: Ps, number of publications; P, percentage in relation to total number of publications in peer-reviewed journals (n = 3,921); *h*, *h*-index; TC, total citations; CA, citation average; AC, article citations; CPP, citation per paper

Table 3 Top 10 authors ranked according to their output in the general field of e-nose research

Rank	Author	Country	Ps	P	*h*	TC	CA	AC	CPP	TLS
1	J Wang	China	88	2.24	31	2,483	28.22	1,518	17.25	381
2	C di Natale	Italy	74	1.89	39	4,118	55.65	2,831	38.26	500
3	A D'Amico	Italy	57	1.45	36	3,365	59.04	2,379	41.74	404
4	R Paolesse	Italy	52	1.33	35	3,153	60.63	2,222	42.73	380
5	JW Gardner	England	50	1.28	31	3,729	74.58	2,708	54.16	106
6	FC Tian	China	44	1.12	17	845	19.20	503	11.43	206
7	M Zhang	China	38	0.97	14	407	10.71	348	9.16	184
8	Y Wang	China	37	0.94	10	404	10.92	375	10.14	361
9	PJ Sterk	The Netherlands	35	0.89	24	1884	53.83	976	27.89	334
10	G Sberveglieri	Italy	35	0.89	25	1,389	39.69	1,094	31.26	161

Notes: Ps, number of publications; P, percentage in relation to total number of publications in peer-reviewed journals (n = 3,921); *h*, *h*-index; TC, total citations; CA, citation average; AC, article citations; CPP, citation per paper, TLS, total link strength

knowledge domain map displayed in Figure 4 shows the contribution of diverse authors to e-nose research, with the size of the corresponding nodal disc indicating the number of articles published in co-authorship and the links between the nodes representing the collaborative networks. In this chart, it is possible to note that the collaboration clusters comprised mainly Chinese, Italian and English researchers.

The top 10 journals, all of which were SCIE-listed, are shown in Supplementary File (Table S1) ranked according to the number of peer-reviewed papers retrieved on the general e-nose topic. The leading periodicals Sensors and Actuators B Chemical (which publishes experimental papers only), Sensors and IEEE Sensors Journal (both of which publish experimental and theoretical papers) are highly specialized in the field of sensor technology, with the first mentioned having published almost to three-times the number of e-nose papers compared with the other two. The aims and scope of the remaining seven journals are much broader covering the technology of sensors along with other fundamental and applied aspects of analytical chemistry/biochemistry associated mainly with the analysis of food products. As expected, most e-nose studies were carried out by researchers in the disciplines of instrument/instrumentation, chemistry analytical and food technology (Supplementary File, Table S1).

The 10 most cited e-nose articles (Ampuero and Bosset, 2003; Battiston *et al.*, 2001; Dickinson *et al.*, 1996; Gardner and Bartlett, 1994; Gutierrez-Osuna, 2002; Machado *et al.*, 2005; McAlpine *et al.*, 2007; Di Natale *et al.*, 2003; Staii *et al.*, 2005; Toal and Trogler, 2006) in the WoS database are listed in the Supplementary File (Table S2) and relate to studies published during the period 1994 and 2007. As expected, the majority of these papers deal with specific applications of e-nose technology, except by the top-ranked article by Gardner and Bartlett (1994), which provide a definition of "electronic nose" and review the history of the technology from its early inception up to 1993. Although many scientists claim that the number of citations is not a reliable measure of quality and performance because it depends on a multitude of factors, author-level metrics are extremely important because they reflect on the reputation of the researcher. The current

Figure 3 Knowledge domain map visualized using VOSviewer of the contributions of organizations to the general area of e-nose research

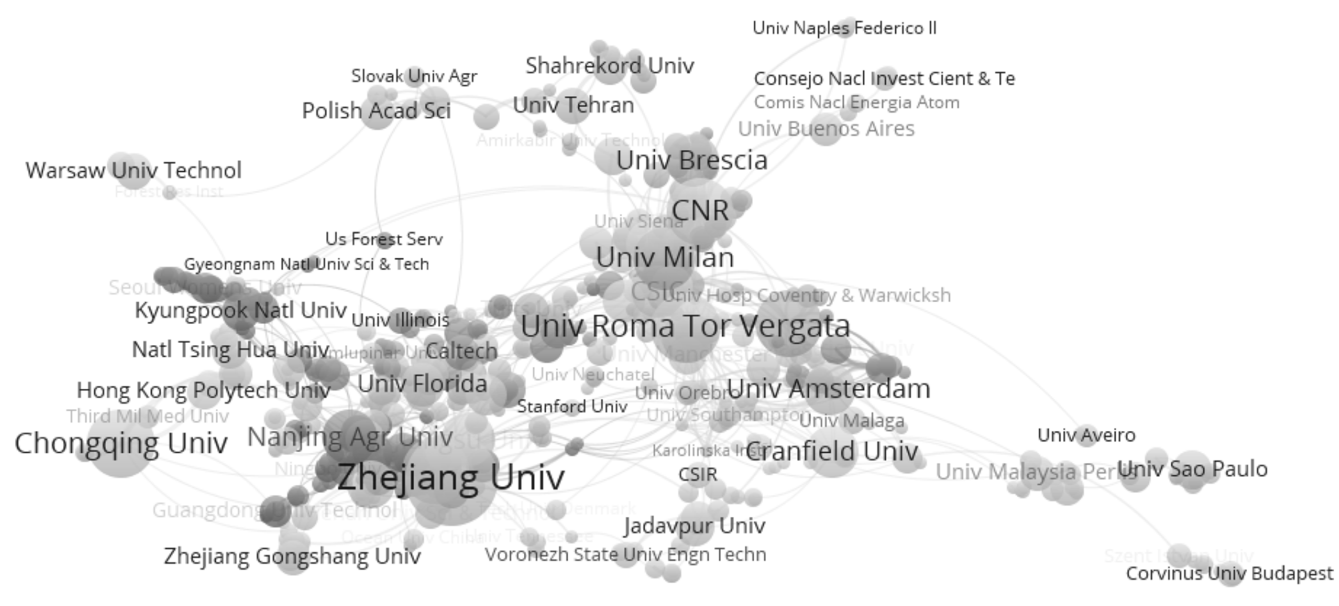
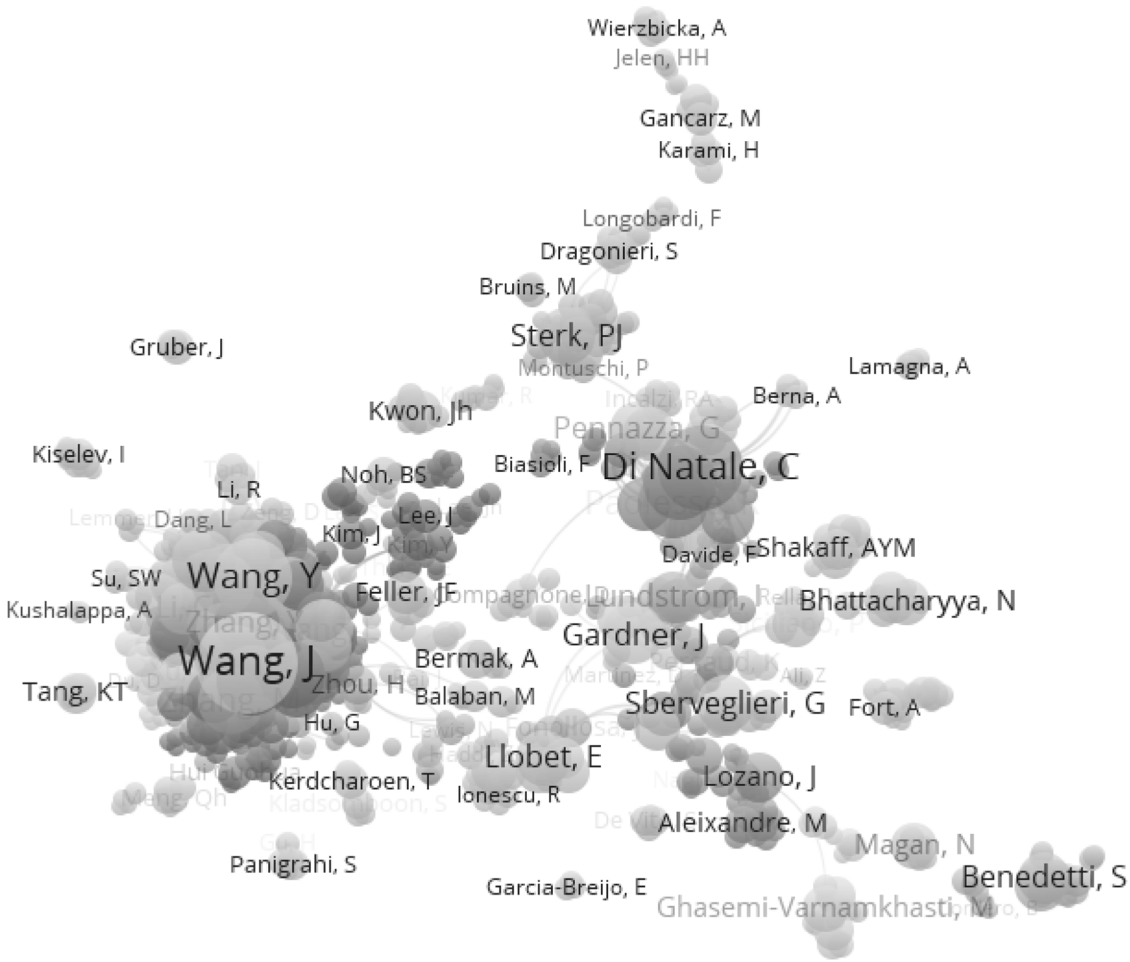


Figure 4 Knowledge domain map visualized using VOSviewer of authors who have published in the general area of e-nose research



consensus among many bibliometricians is that comparisons should only be made between papers of similar age and covering analogous fields (van Noorden *et al.*, 2014). For this reason, we chose to focus only on articles retrieved from peer-reviewed SCIE-indexed journals for the bibliometric analysis of publications on fuel-related e-nose applications described Section 3.3.

The incidents of occurrence of the main keywords employed in the documents retrieved from WoS are shown in the Supplementary File (Figure S1) in which the font size is directly proportional to frequency. During the timeframe 1993–2021, the frequency of occurrence of particular keywords decreased in the order: electronic nose > volatile organic-compounds > gas sensor > sensors > classification > sensor array > analysis. However, the utilization of these keywords was practically constant in all period, with a little peaked around 2017 and has the single exception of the term “electronic nose”, which has increased consistently their use over the years (Supplementary File, Figure S2). The alterations observed in the frequency of particular keywords likely reflect changes in research objectives, as many of the articles retrieved in the general search were related to food studies, with increasing emphasis on technology used rather than to the application to quality assessment. In addition, changes in keywords have been associated with the introduction of sophisticated algorithms by which contemporary search engines find target information in online databases by scanning terms in the title, abstract and, sometimes, within the text. Hence, many journals now recommend that keywords should not duplicate terms found in the title or abstract.

3.3 Quantitative analysis of the search performed using fuel-related e-nose descriptors (Steps 3 and 4)

A targeted search of the 3,921 e-nose papers retrieved from the WoS using descriptors specific to fuel-related applications captured 72 articles from 220 authors and 94 research organizations distributed over 21 countries and indexed according to 226 keywords. The knowledge domain map (visualized with VOSviewer) presented in Figure 5 shows that, with the exception of China, Spain and USA, countries that led in the fuel-related area of e-nose research (namely, India, Poland, Brazil, Israel, Germany, Sweden and France) were different from those that led in general e-nose investigations. The most striking feature of this diagram is that there appear to be few links between the countries, demonstrating that international collaborative research in the field of fuel-related e-nose applications was somewhat limited.

Figure 5 Knowledge domain map visualized using VOSviewer of the contributions of countries to the field of fuel-related e-nose applications

The results outlined in Figure 5 are compatible with the locations of the top 10 research organizations engaged in fuel-related e-nose studies (Figure 6 and Table 4). In terms of numbers of publications, the Universidad de Cádiz, the Defence Research Development Organisation and the Universidade de São Paulo led the ranking. However, most fuel-related e-nose investigations appear to have been performed independently with little international collaboration between organizations, a situation that may be related to the differential energy matrices that predominate in each country. Nevertheless, collaborative research is a very important aspect of the scientific endeavor by virtue of the alternative approaches that may be introduced by other investigators with dissimilar backgrounds, experiences and viewpoints.

The most prolific authors in fuel-related e-nose research are shown in the knowledge domain map presented in Figure 7 and, as expected, they were affiliated to institutions and countries with the highest levels of investigative activity in this area (Table 4). Although there are clusters of collaboration among researchers within the various countries, international collaboration appears to be generally negligible. Consistent with the results from the more general search, Sensors, Sensors and Actuators B Chemical and IEEE Sensors Journal led the list of ten journals that had published the largest number of articles relating to fuel-related e-nose field, and most of these studies had been carried out by experts in the disciplines of electronics/instrumentation, analytical chemistry and electrical/electronic engineering (Supplementary File, Table S3). The frequency of occurrence of keywords presented in the Supplementary File (Figure S3) reveals that the main terms used to draw attention to papers in this area were electronic nose, chemometrics, gasoline and characterization.

However, various other terms such as classification, fingerprints, sensor, sensor array, weathering, artificial neural networks, chemical sensors and diesel also occurred with some frequency.

3.4 Qualitative analysis of the main articles associated with fuel-related e-nose applications

Table 5 lists the 22 articles describing the application of e-nose to fuel-related products published over the past ten years and selected on the basis of relevance to the present analysis (Aliaño-González *et al.*, 2018a, 2018b; Amini and Hosseini-Golgoo, 2012; Bieganowski *et al.*, 2018; Calle *et al.*, 2020; Falatová *et al.*, 2018, 2021; Ferreiro-González *et al.*, 2016, 2017; Hong, 2018; Kumar *et al.*, 2020; López *et al.*, 2016; Mahmodi *et al.*, 2019; Mumyakmaz and Karabacak, 2015; Nozza *et al.*, 2016; Osowski and Siwek, 2017; Singh *et al.*, 2016; Siqueira *et al.*, 2018, 2019; Song *et al.*, 2011; Vidigal *et al.*, 2021; Wu *et al.*, 2020). Among these papers, 10 (45.5%) were published in the periodical sensors, whereas the remainder were distributed over a diverse range of journals. A total of 15 articles (68.1%) were classified in the discrimination group (Aliaño-González *et al.*, 2018a; Amini and Hosseini-Golgoo, 2012; Bieganowski *et al.*, 2018; Calle *et al.*, 2020; Falatová *et al.*, 2018, 2021; Ferreiro-González *et al.*, 2016, 2017; Kumar *et al.*, 2020; Mahmodi *et al.*, 2019; Osowski and Siwek, 2017; Singh *et al.*, 2016; Siqueira *et al.*, 2018, 2019;

Table 4 Top 10 organizations ranked according to their output in the field of fuel-related e-nose research

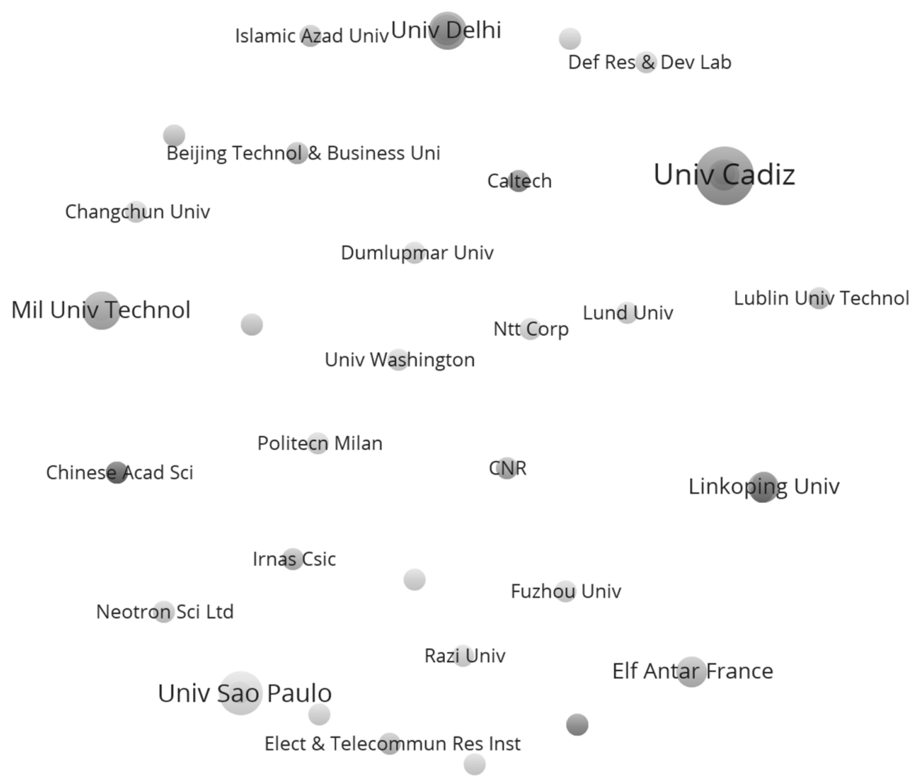
Rank	Organization	Country	Ps	P	*h*	TC	CA	AC	CPP
1	Universidad de Cádiz	Spain	7	14.89	5	55	7.86	32	4.57
2	Defense Research Development Organization (DRDO)	India	4	8.51	2	62	15.50	60	15.00
3	Universidade de São Paulo	Brazil	4	8.51	3	25	6.25	22	5.50
4	Linkoping University	Sweden	3	6.38	3	37	12.33	37	12.33
5	Military University of Technology in Warsaw	Poland	3	6.38	3	53	17.67	53	17.67
6	Solid State Physics Laboratory (SSPL)	India	3	6.38	2	60	20.00	58	19.33
7	University of Delhi	India	3	6.38	2	60	20.00	58	19.33
8	Warsaw University of Technology	Poland	3	6.38	3	53	17.67	53	17.67
9	Elf Antar France	France	2	4.26	2	30	15.00	28	14.00
10	Elf Aquitaine Co.	France	2	4.26	2	30	15.00	28	14.00

Notes: Ps, number of publications; P, percentage in relation to total number of articles published in peer-reviewed indexed journals (n = 47); *h*, *h*-index; TC, total citations; CA, citation average; AC, article citations; CPP, citation per paper

Song *et al.*, 2011), five articles (22.7%) were classified in the prediction group (Hong, 2018; López *et al.*, 2016; Mumyakmaz and Karabacak, 2015; Nozza *et al.*, 2016; Vidigal *et al.*, 2021) and the remaining two studies (Aliaño-González *et al.*, 2018b; Wu *et al.*, 2020) could be classified in both groups.

The full set of papers within the discrimination group used a range of statistical techniques to distinguish the e-nose profiles of the samples as follows: 9 used principal component analysis (PCA) (Aliaño-González *et al.*, 2018b; Bieganowski *et al.*, 2018; Falatová *et al.*, 2018; Ferreiro-González *et al.*, 2017; Kumar *et al.*, 2020; Osowski and Siwek, 2017; Singh *et al.*, 2016; Siqueira *et al.*, 2018; Wu *et al.*, 2020), 9 used linear discriminant analysis (LDA) (Aliaño-González *et al.*, 2018a, 2018b; Amini and Hosseini-Golgoo, 2012; Calle *et al.*, 2020; Falatová *et al.*, 2018, 2021; Ferreiro-González *et al.*, 2016, 2017; Mahmodi *et al.*, 2019), 7 used artificial neural networks (ANN) (Amini and Hosseini-Golgoo, 2012; Bieganowski *et al.*, 2018; Kumar *et al.*, 2020; Singh *et al.*, 2016; Siqueira *et al.*, 2018; Song *et al.*, 2011; Wu *et al.*, 2020), 7 used hierarchical clustering analysis (HCA) (Aliaño-González *et al.*, 2018a, 2018b; Calle *et al.*, 2020; Falatová *et al.*, 2018, 2021; Ferreiro-González *et al.*, 2016, 2017), 3 used quadratic discriminant analysis (QDA) (Mahmodi *et al.*, 2019; Siqueira *et al.*, 2018, 2019), 3 used support vector machine (SVM) (Mahmodi *et al.*, 2019; Osowski and Siwek, 2017; Song *et al.*, 2011) and 3 used

Figure 6 Knowledge domain map visualized using VOSviewer of the contributions of organizations to the field of fuel-related e-nose applications



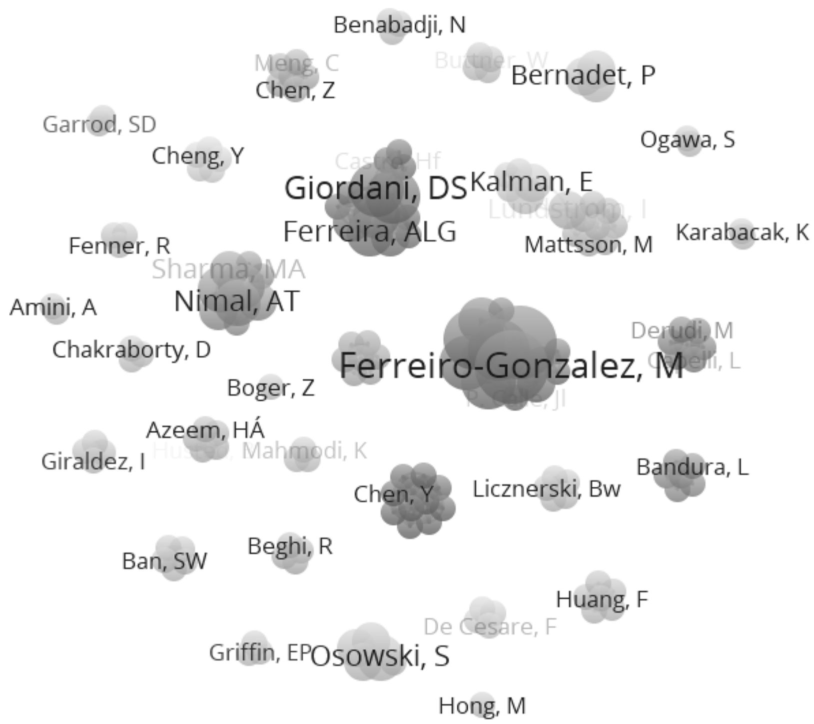


Figure 7 Knowledge domain map visualized using VOSviewer of authors who have published in the field of fuel-related e-nose applications

stochastic analysis (Siqueira *et al.*, 2018, 2019; Vidigal *et al.*, 2021). Other methods mentioned were autoregressive moving average with exogenous inputs (ARMAX) (Amini and Hosseini-Golgoo, 2012), wavelet analysis (Osowski and Siwek, 2017) and random forest analyses (Osowski and Siwek, 2017).

Within all articles classified in the prediction group, four papers predicted the concentration of gases and volatile vapors using simple linear regression (Wu *et al.*, 2020), multiple linear regression (Vidigal *et al.*, 2021), mass balance model/confidence intervals (Nozza *et al.*, 2016) or ANN (Mumyakmaz and Karabacak, 2015). In addition, Hong (2018) applied mathematical modeling to e-nose profiles to detect and recognize three types of volatile gases and evaluated the transient responses from four sensors and from the wireless sensor matrix, whereas Aliaño-González *et al.* (2018b) applied nonlinear regression to e-nose olfactory profiles to analyze samples of gasoline weathered at different times on various types of support (cork, wood, paper and cotton sheet). In the ultimate paper of this group, López *et al.* (2016) determined the qualitative and quantitative relationships between e-nose patterns and the compositions of compost and composting gases/volatile organic compounds (VOCs) at an industrial scale plant using PCA and partial least squares regression with the aim of assessing compost quality and maturity. The majority of these studies used a number of methods, applied either sequentially or comparatively, for data analysis.

Fuel-related e-nose studies published in the past 10 years aimed mainly at the discrimination of samples containing gas mixtures and, on a smaller scale, the quantification of VOCs. The qualitative analysis of samples by e-nose has already been recognized as a reliable and rapid method, as it is based on the ΔR value, which expresses the difference between the maximum and minimum resistance values of each sensor used to obtain an olfactory profile of the target mixture. However, the quantitative analysis of fuel samples has been more difficult because of modeling complexity. Some machine-learning techniques, including ANN and SVM, have been commonly used in the analysis of e-nose data, but their application to fuel-related products is not practical because of the cost and time required to obtain the large numbers of samples needed for training and validating the e-nose. A few studies identified in the present search applied machine-learning techniques but used these techniques in a relatively small number of samples, for example, 18–20 for ANN (Kumar *et al.*, 2020; Singh *et al.*, 2016). Recent advances in data analysis may have overcome these problems where the sample size is too small for the application of such methods. Siqueira *et al.* (2018) reported a stochastic model demonstrating that, in addition to ΔR, it is possible to extract more information from the signals produced by e-nose sensors. In this model, each signal is quantified through five different parameters and these provide information about the transient and stationary regimes as well as the signal noise. The authors demonstrated that there is not only a physical interpretation of the value of each of these parameters but that the combination of values is proportional to the concentration of VOCs in the sensor region. This approach should allow the quantitative analysis of samples, increase the power of analysis for each sensor, and enable the use of e-noses with fewer sensors. An example of the application of this model has been reported by Vidigal *et al.* (2021) who described the quantification of oxidative stability of biodiesel samples and the excellent agreement of the e-nose method in relation to conventional methods of analysis of VOCs. Then, the stochastic model (Siqueira *et al.*, 2018, 2019;

Table 5 The 22 Recently published (2011 – 2021) papers selected for their relevance to fuel-related e-nose applications

Reference	No. of groups (number of samples)	Objectives	Methodology applied (percentage accuracy) [a]
Wu *et al.* (2020)	5 groups: ethanol (5), tetrahydrofuran (5), turpentine (5), lacquer (5), gasoline (5)	To quantify gas concentration	Univariate regression: average error 9.1%–18.4%
	5 groups: ethanol (12), tetrahydrofuran (12), turpentine (12), lacquer (12), gasoline (12)	To distinguish the samples	PCA (could not distinguish samples satisfactorily) *vs* BP-ANN (100%)
Kumar *et al.* (2020)	3 groups: DMMP (4), diesel (3), DMMP and diesel mixture (11)	To detect traces of nerve agent simulant in the fuel vapor environment	PCA (separated the sensor responses for the individual vapors as well as their combination) *vs* ANN (100%)
Siqueira *et al.* (2018)	2 groups: domestic WCO (44) and commercial WCO (44)	To classify samples according to their origin	PCA + QDA (58%–60.2%) *vs* QDA: 63.6% *vs* ANN (61.3%–67%) *vs* Stochastic model + QDA: 91.6%
Vidigal *et al.* (2021)	9 groups: 8 stored samples and 1 fresh sample. 5 replicates for each group	To explain and predict the oxidative stability of biodiesels by olfactive profile	Multiple linear regression + PCA (could not distinguish samples satisfactorily) *vs* Multiple linear regression with parameters of stochastic model (R^2: 84%–91%)
Falatová *et al.* (2021)	360 groups (6 x 2 x 5 x 6): 6 substrates (vinyl, linoleum, polyester, polyamide carpet, cotton, cork) x 2 materials (cotton and cork) x 5 ignitable liquids (gasoline, diesel, ethanol, charcoal starter with kerosene and control) x 6 times (after 10 min, 1, 6, 12, 24, and 48 h) 1 replicate in each group	To identify the presence or absence of ignitable liquid residues (ILRs) and to investigate whether headspace–mass spectroscopy electronic nose (HS-MS e-nose) combined with pattern recognition can be used to classify different ILRs	HCA + LDA (100%)
Calle *et al.* (2020)	50 groups: ((3 × 3 + 1) × 5): [(3 ILs (diesel, gasoline, and kerosene) × 3 commercial brands) + Control] × 5 different times (0, 2, 5, 13 and 38 days) 2 replicates for each group	To investigate the potential of using ion mobility sum spectrum (IMSS) for the characterization of different ILs biodegraded at different levels within soil samples	HCA: did not achieve a precise separation of all the samples, they present a grouping trend that is based on IL type. LDA: 99% of the samples successfully discriminated
Mahmodi *et al.* (2019)	2 groups: pure fuel (90), impure fuel (375)	To classify fuels as pure or impure	QDA (84.4%) *vs.* LDA (75.5%) *vs.* SVM (94.3 – 97.5%) In total: 310 for training and 155 for testing
	6 groups: canola oil with methanol (15), corn oil with methanol (15), Canola oil with ethanol + corn oil with methanol (15), Canola oil with ethanol (15), corn oil with ethanol (15), gasoline (15)	To classify fuels into their 6 groups	QDA (~90 – 98%) *vs.* LDA (~80 – 95%) *vs* SVM (71.4%–100%) In each group: 10 for training and 5 for testing
	31 groups (6 + 25): 6 pure fuels (diesel, canola methyl ester, corn methyl ester, canola ethyl ester, corn ethyl ester, canola ethyl ester/corn methyl ester) + 25 mixtures of 5 types of biofuels in 5 levels. 15 replicates each group	To classify the various pure biofuels and their mixtures	SVM (71.4%–100%)
Siqueira *et al.* (2019)	2 groups: domestic WCO-based biodiesel (18) and pure cooking oil-based biodiesel (18)	To predict the compliance of synthesized biodiesels with the specifications of the Brazilian Petroleum Authority (ANP)	Stochastic model + QDA (80%–92%)

(***continued***)

Table 5

Reference	No. of groups (number of samples)	Objectives	Methodology applied (percentage accuracy) [a]
Bieganowski *et al.* (2018)	31 groups (10 x 3 + 1): 10 soil types: brunic arenosol, stagnic luvisol, haplic cambisol, leptic cambisol, mollic stagnic fluvisol, stagnic phaeozem (siltic), haplic chernozem (siltic), haplic luvisol (siltic), leptic skeletic dystric cambisol, haplic fluvisol (clayic) x 3 treatments (without contamination, contamination with diesel, and contamination with petrol) + control group (empty cylinder) 24 replicates in each group	To detect soil contamination and to distinguish between pollutants and contamination levels	PCA + BP-ANN (validation over 95%)
Aliaño-González *et al.* (2018a)	25 groups (3 × 4 x 2 + 1): 3 petroleum-derived products (PDPs; gasoline RON95, normal diesel and commercial liquid paraffin Zibro Fire) × 4 substrates with dissimilar porosities (pine wood, natural cork, paper and cotton sheet) × 2 volumes (40 μL and 80 μL) 18 replicates in each group) + control group (12)	To identify the presence/absence of different PDPs in diverse substrates	HCA (85.5%) *vs* LDA (97.7%)
Falatová *et al.* (2018)	2 groups: presence (36) and absence (36) of gasoline in weathered fire debris samples	To discriminate between fire debris samples with and without gasoline	HCA (100%) *vs* PCA + LDA (100%)
	3 groups: carpet/gasoline (12), carpet/ gasoline/powder (12) and carpet/gasoline/cafoam (12)	To discriminate carpets with/without different substances	PCA + LDA (80.6%)
Hong (2018)	6 groups (3 x 2): 3 kinds of oil (diesel, lubricating oil and engine oil) x 2 concentrations (high and low) 1 replicate in each group	To optimize an algorithm for a portable electronic nose aiming at oil detection	Mathematical modeling (not applicable)
Aliaño-González *et al.* (2018b)	8 groups (2 x 4): 2 different volumes of gasoline (40 and 80 μL) x 4 different substrates (pine wood, cork, paper and cotton sheet) 9 replicates in each group	To discriminate samples of weathered gasoline	HCA (inconclusive) *vs* PCA + LDA (100%)
	4 groups: pine wood (18), cork (18), paper (18) and cotton sheet (18) substrates	To evaluate the degradation rate of gasoline in different substrates	Nonlinear regression ($R^2 = 0.711 - 0.825$)
Ferreiro-González *et al.* (2017)	4 groups: gasoline (9), diesel (9), ethanol (9) and aromatics (9) + empty units (3)	To characterize and differentiate petroleum-derived products	HCA + PCA + LDA (100%)
Osowski and Siwek (2017)	12 groups (3 × 4): 3 gasoline additives [ethanol, ether (3% MTBE + 97% ETBE) and benzene] × 4 proportions of each additive (5, 10, 15 and 20% volume) 72 replicates in each group	To analyze the noisy signal patterns generated by an electronic nose towards different gasoline additives	CWTA algorithm (66.7 –100%) *vs* PCA (good prognostic for accurate recognition and separation of all classes) *vs* wavelet transformation (not applicable) *vs* SVM [5.12% mean error (7 sensors) and 5.8% (6 sensors)] *vs* Random Forest [19.87% mean error (7 sensors) and 21.14% (6 sensors)]
Singh *et al.* (2016)	4 groups: benzene (5), methanol (5), diesel (5) and DMMP (5)	To detect and classify the target vapors.	PCA + ANN (100%) In each group: 3 for training and 2 for testing

(***continued***)

Table 5

Reference	No. of groups (number of samples)	Objectives	Methodology applied (percentage accuracy) [a]
Ferreiro-González *et al.* (2016)	7 groups of ignitable liquids: gasoline (8), diesel (9), kerosene (9), citronella (8), paraffin (10), ethanol (7), none (11)	To determine the most suitable spectroscopic signals for the discrimination of ignitable liquids	HCA (100%) *vs* LDA (100%)
Nozza *et al.* (2016)	2 groups: 2 test cycles 15 replicates in each group	To predict indoor air quality	Modeling (mass balance) + range (dashed lines represent a deviation of ±20% from the ideal values): in general, high recognition performances were achieved
López *et al.* (2016)	7 groups of industrial compost piles: garden pruning (GP) 106 days, GP with fine materials from biomass (FM) 145 days, GP with rice husks 423 days, GP 510 days, FM 58 days, FM 111 days, horse manure 500 days	To establish qualitative and quantitative relationships between compost maturity (gas emissions) and e-nose patterns	PCA + PLS (not available)
Mumyakmaz and Karabacak (2015)	6 groups (3 + 3): 3 gases – methane, hydrogen, and carbon monoxide (10 different concentrations of each gas in dry air) + 3 binary mixtures of carbon monoxide and methane (5 different concentrations of CO in each mixture)	To predict the concentrations of combustible and toxic gases in the environment	3 ANN with Levenberg–Marquardt algorithm (R correlation coefficient 0.99864 – 1) In total: 37 for training and 9 for testing
Amini and Hosseini-Golgoo (2012)	6 groups: methanol (16), ethanol (16), 1-butanol (16), iso-butanol (16), acetone (16), hydrogen (16)	To discriminate samples	ARMAX model + ANN (100%) *vs.* ARMAX model + LDA (2D and 3D; 93%) In each group: 11 for training and 5 for testing
	9 groups: methanol (16), ethanol (16), 1-propanol (16), 2-propanol (16), 1-butanol (16), 2-butanol (16), iso-butanol (16), acetone (16), hydrogen (16)	To discriminate the analytes using a generic tin oxide gas sensor with a heating element driven by a fast staircase voltage waveform.	ARMAX model + ANN *vs.* ARMAX model + LDA (2D and 3D): successful discrimination of analytes, except for 2-propanol and 1 butanol In each group: 11 for training and 5 for testing
Song *et al.* (2011)	19 groups ($4 \times 5-1$): 2 gases (hydrogen, methane) × 5 concentrations (0, 1,000, 3,000, 5,000 ppm), omitting the 0:0 ppm combination	To detect combustible methane and hydrogen and estimate their concentrations, either singly or in mixtures	LS-SVR (Correlation coefficient = 0.9948 and 0.9981; training time = 0.0238 s) *vs* SVR (Correlation coefficient = 0.9925 and 0.9990; training time = 12.844 s) *vs* BP-ANN (Correlation coefficient = 0.9944 and 0.9972; training time = 115.994 s)

Notes: ANN: artificial neural network; ARMAX: autoregressive moving average with exogenous inputs; BP-ANN, back propagation-artificial neural network; CWTA, continuous wavelet transform algorithm; DA, discrimination analysis; DMMP, dimethyl methylphosphonate; HCA, hierarchical cluster analysis; LDA, linear discriminant analysis; LS-SVR, least square support vector regression; LVQ, learning vector quantization; MLP, multilayer perceptron; PCA, principal components analysis; PDP, petroleum derived products; PLS, partial least squares regression; QDA: quadratic discriminant analysis; RBF: radial basis function; SVM: support vector machine; WCO, waste cooking oil, [a] Methods linked with a plus sign (+) represent a sequential procedure, whereas those linked with versus (*vs*) denote a comparative procedure

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Vidigal *et al.*, 2021) has been shown as a hopeful alternative and capable of providing an acceptable methodology since it delivers good results with low amount of samples.

3.5 Perspectives and trends

From the results presented in this work, it is clear that the electronic nose is not so used in the analysis of fuels and biofuels. The detection properties in fuels are an analytically difficult task because of the necessity of detecting a combination of a variety of components, instead of detecting the presence of a single substance, but e-noses can detect the fingerprint formed by this combination, which paves the way for smaller, but efficient and cheaper instruments (Wojnowski *et al.*, 2017).

The use of data produced by a single sensor is usually insufficient for analyzes based on e-noses and constitutes the main barrier for the technology to develop. Some works aim to combine data from various types of sensors (Di Rosa *et al.*, 2017) or they propose innovations with a series of sensors in sequential sets, called electronic mucosa systems (Deshmukh *et al.*, 2015), but these technologies make analysis more expensive. These problems cannot be overcome unless an innovative pattern detection technique is able to extract more data from a single sensor.

The discovery and characterization of the family of genes that encode olfactory receptors will contribute to the elaboration and development of electronic smell systems, the so-called bioelectronic noses. Olfactory receptors will be used as a biological element in this type of instruments, which naturally still require an interface for acquiring the signals produced and a data interpretation system (Wasilewski *et al.*, 2017).

Solutions to produce high sensitivity sensors, such as the hybridization of carbon nanotubes with fullerene structured in a 3D architecture by spray layer-by-layer which allows to significantly boost the sensitivity of sensors to reach the sub-ppm level (Nag *et al.*, 2017), will certainly contribute to the development of more effective and selective equipment.

Despite all the technological development concerning the most modern and most sensitive sensors, we believe that the use of simple and inexpensive sensors (Murugan and Gala, 2017) combined with powerful data interpretation methodologies (Siqueira *et al.*, 2018) are the way to develop portable, accurate and reliable e-noses.

4. Conclusions

Although there are more than 6,000 documents, being 4,000 articles relating to e-nose studies, less than 2% of then are articles on fuel related e-nose applications. Furthermore, the results presented herein show that 15 (68.2%) of the 22 selected articles dealing with fuel-related e-nose applications were published within 2017–2021, denoting that this research topic is still in its embryonic stages and there are a great, to be explored, potential.

The results of the search, performed using general e-nose descriptors, showed that the countries having greater number of publications about this subject are China, Italy, EUA, England and Spain. From Figures 2–4, it is possible to verify the existing interaction between countries, organizations and authors. However, when the field of fuel-related e-nose applications is considered, a completely different scenario raises up (Figures 5–7), being possible to be observed that there is no interaction between countries and organizations, there are not many authors and they work in small groups, without interaction between these groups. This minimal national and/or international collaboration between researchers and institutions can be explained, besides this subject is still very recent, by the diverse profiles of energy among the various countries around the world. Nonetheless, the general move away from fossil fuels in favor of a mix of renewable energy resources (geothermal, solar, hydro, wind, etc.) will be possibly accompanied by an increase in use of biofuels in the transport sector, particularly for lower-income countries and/or those with large land areas. As a natural consequence, collaborations concerning fuel-related products are likely to increase as well, including those related to e-nose applications. The sharing of know how among researchers/institutions, as the knowledge about sensors characteristics and/or building of equipment and/or techniques for modeling of olfactive profile is expected to boost innovation and bring long-lasting practical benefits to all companies involved in fuel-related activities.

E-noses can be cost effective tools on detecting the fingerprint formed by a broad combination of substances and the stochastic technique has been promising in processing of olfactive profile data. Moreover, with the recent overcoming of the modeling barrier, there is a wide range of research opportunities for the detection, quantification and prediction of VOCs in biofuels using e-nose equipment.

We expect that this work instigates researchers to collaborate in this full of opportunities area, increasing the research community and consequently, the dissemination of new findings.

Supplementary material

The supplementary material for this article can be found online.

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