Construction and Building Materials 485 (2025) 141906

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat

Potential use of an olfactory machine to rapidly differentiate various commercial thermally-modified Scots pine wood products

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ARTICLE INFO

Keywords:
Thermally modified wood
Volatile organic compounds
Olfactory machine
Electronic nose

ABSTRACT

Differentiating thermally modified wood types based on appearance alone is challenging. The primary objective of this study was to accurately identify and rapidly differentiate various commercial thermally-modified Scots pine wood products using an olfactory machine, in order to avoid profiteering and fraud in the trade. For this purpose, ThermoWood® (Thermo-D class), oil-heat treated wood (OHT) and Termovuoto® were used. The machine utilized for this study was outfitted with six metal oxide semiconductor (MOS) sensors classified as electrochemical sensors. Data analysis using principal component analysis (PCA) and linear discriminant analysis (LDA) demonstrated that the olfactory machine could differentiate thermally modified wood products from untreated wood with 100 % accuracy. Furthermore, the system effectively distinguished among the modified woods despite some overlap between ThermoWood® and Termovuoto®. The findings highlight the olfactory machine's effectiveness in replacing traditional methods and in identifying thermally modified wood products, providing a quick and reliable tool for the wood industry to combat fraud and ensure product authenticity.

1. Introduction

Thermal modification of wood as an environmentally friendly process, which is typically performed in an oxygen-controlled environment at temperatures ranging from 160 °C to 220 °C alters the physical, chemical, and mechanical properties of wood [1]. It generally leads to an increase in dimensional stability and durability, while often reducing mechanical strength [1,2]. There are various commercial processes like ThermoWood®, oil-heat treated wood (OHT), and Termovuoto®, which are mainly different in their processing methods, conditions, properties and intended application. The OHT process which was developed in Germany around 2000, typically uses vegetable oils as a heat transfer medium in a closed vessel [3]. The ThermoWood® process developed in the 1990s in Finland generally involves heating wood at high temperatures in the presence of steam. The Thermovuoto® process was developed more recently as an EU-Eco-Innovation initiative project by the National Research Council of Italy and the Swedish University of Agricultural Sciences (SLU) [4]. This approach, also known as the thermo-vacuum process, uses forced airflow to produce heating and a partial vacuum to replace the oxygen in the reactor [5]. According to Hill (2006), the continuous operation of the vacuum removes volatile compounds from the furnace which contributes to a lower rate of wood mass loss compared to ThermoWood® [6]. The reader can refer to Esteves, Sandberg et al. and Hill et al. to obtain more information about the thermal modification processes of wood [1,7,8].

Colorimetric analysis has been explored as a potential indicator to

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https://doi.org/10.1016/j.conbuildmat.2025.141906
Received 25 March 2025; Received in revised form 5 May 2025; Accepted 19 May 2025
Available online 24 May 2025
0950-0618/

detect the thermal modification process of wood [9]. The inherent complexity of wood, arising from a great number of influencing anatomical factors such as annual ring width, sap- heartwood, reaction wood, significantly impacts the material's color properties, thereby posing a challenge for accurate detection. Therefore, it can be claimed that it is almost impossible to identify various types of thermally modified wood products based only on their visual features, such as color and texture. For this reason, profiteering and fraud may occur in the trade. Some identification techniques like olfactory machine may be helpful to quickly and accurately identify these types of modified wood products [10]. Machine learning (ML) approach as a subset of artificial intelligence (AI) was also recently used by Liu et al. (2024) to predict the stiffness and hardness of wood after thermal modification [11].

Thermal modification induces substantial chemical alteration in wood, including deacetylation and depolymerization of hemicelluloses, hydrolysis and partial depolymerization of cellulose, and degradation and condensation of lignin [1]. These chemical changes lead to the emission of various volatile organic compounds (VOCs) such as terpenes, phenols, aldehydes, and carboxylic acids [12]. Olfactory machine or electronic nose (e-nose) system is a new analytical technique that can recognize the odor profile of various materials [13–16]. This system is based on a metal oxide semiconductor multi-sensor in order to create a fast, sensitive and reliable method for classifying different scents. By simulating the human sense of smell, the olfactory machine detects complex odors using an array of chemical sensors [16]. When odor molecules hit the sensors, chemical or physical reactions occur between the molecules and the sensor surface, leading to changes in the electrical properties or other characteristics of the sensor. The changes are then converted into electrical signals [17], which indicate the concentration and type of chemical compounds in the odor sample [18]. Finally, the collected data are analyzed by signal processing algorithms, such as machine learning algorithms or statistical methods [19,20]. Compared to traditional analytical techniques such as gas chromatography (GC) and liquid chromatography (HPLC), the olfactory machine is portable and less expensive. It is also able to simultaneously assess a wide range of odors and determine the overall smell of a sample rather than just identifying individual components [10]. Also, the olfactory machine can identify a mixture of volatile organic samples without the need for independent identification of the volatiles [21]. Thus, olfactory machines are useful in industries where odor detection plays a critical role, such as food quality control [20].

Few studies have been conducted regarding the use of olfactory machines in the wood industry. Sun et al. (2018) investigated the odor emitted from thermally modified bamboo with an olfactory machine and showed that unlike other analytical tools, the electronic nose can identify a mixture of volatile organic components without the need for identification of individual volatiles [22]. Nikoutadbir et al. (2023) found that an olfactory machine equipped with six metal oxide semiconductor sensors is able to identify and separate Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) woods with 100 % accuracy [23]. Culleré et al. (2013) showed that gas chromatography-olfactometry (GC-O) can be used to evaluate the odorants emitted from thermally modified wood, providing valuable information for identifying different types of wood based on their aroma profiles [24]. The main objective of the present study was to use an olfactory machine to detect and separate various types of thermally modified wood products.

2. Materials and methods

2.1. Materials

ThermoWood® (Thermo-D class), oil-heat treated wood (OHT) and Termovuoto® of Scots pine wood (*Pinus sylvestris*) modified at around 212 °C for 2 hours with dimensions of 50 (length) × 50 (width) × 25 (thickness) mm was used. Untreated wood specimens were also used for comparison. ThermoWood® and OHT were manufactured from Russian Scots pine wood, whereas Termovuoto® were produced from Turkish wood. OHT was produced in a pilot-scale reactor at a local private company (Wood Preservers of Persia©). After loading the reactor with sawn timber, soybean oil at ambient temperature was pumped from the reservoir tank into the heated reactor until the wood was completely submerged. The treatment was carried out in an open system under atmospheric conditions. ThermoWood® was produced in an industrial kiln belonging to MazandChoob Arya Co. based on the Thermo-D class through a patented process developed in Finland by the VTT Technical Research Centre. The ThermoWood® process uses steam as a protective medium during high-temperature treatment. The International Association of Wood Anatomists (IAWA) list of microscopic features was employed to identify the thermally modified wood species used.

The wood specimens were equilibrated in a climate room at a relative humidity (RH) of 65 % and a temperature of 20 °C for two weeks prior to the use of olfactory machine. More than 45 days had passed between the time the thermally modified wood products were produced and the time they were used by the olfactory machine. The specimens were cut from the interior of the products to have more VOCs concentration.

2.2. Olfactory machine

The olfactory machine is designed to identify and differentiate odors or VOCs in a manner similar to the human sense of smell. This device typically consists of gas sensors that react to a variety of compounds. The response patterns from these sensors are analyzed using data processing algorithms to determine the category to which a specific sample belongs. In the wood industry, particularly with thermally modified woods, the olfactory machine can detect subtle differences in the composition of volatile gases that arise from variations in processing or potential fraud. To improve the robustness and accuracy of sensor output, a differential method is employed to eliminate noise or drift in the sensor responses. After this preprocessing step, the data is analyzed using various methods, ultimately leading to the evaluation of the sample.

The developed electronic nose system (E-nose) comprises a chamber of samples and sensors, a diaphragm pump, a power supply, a carbon filter, and a data acquisition board (Fig. 1). Six holes with a diameter of 2 mm at equal intervals were made in the cap of the olfactory machine. The sensors' compartment includes 6 metal oxide semiconductor (MOS) arrays (Hanwei Electronics Co., Ltd., Henan, China) and each one reacts most to a particular odor. The sensors are able to convert a chemical quantity into an electrical quantity which is necessary for analysis of VOCs. In fact, the resulting electrical response of each sensor is unique to a specific odor, which is called an odor fingerprint [25]. Specifications of the utilized sensors are demonstrated in Table 1.

A static-400 mL chamber was considered to place samples and sensors in it. The electronic board of the sensors array was mounted on the chamber's lid where some holes were made so that the air could be ventilated to clean the container. The developed system was equipped with two 12 V air/water diaphragm pumps to remove odor from the container. Two 5 V and 12 V power supplies provided the required electric power in the developed system, the former delivers power to the pumps and the latter to the sensors. Finally, controlling the pumps was conducted using a 12 V R12–02 relay. The data were collected in the laboratory at a temperature of 25 °C and a relative humidity of 40 %.

The response of the olfactory machine sensors is indicated by a change in resistance over time (Fig. 2) The measurement process is divided into three different steps: baseline correction (R0), measurement (Rmax) and finally cleaning the chamber. Depending on the stage of the system, air is channeled through different circuits by means of valves that are controlled by a computer program [10]. Principal component analysis (PCA) was applied to analyze the obtained data. Support vector machine (SVM) and Linear discriminant analysis (LDA) methods were then used to determine the accuracy of samples classification by Unscrambler X 10.4 (64-bit) software.

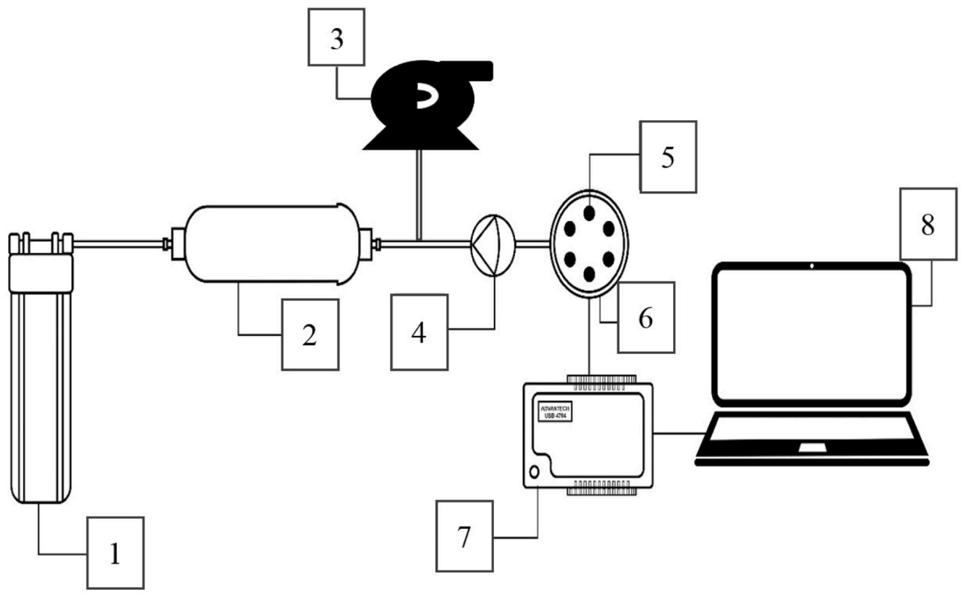

Fig. 1. Schematic view of the electronic nose system (E-nose), 1. Air filters 2. Carbon filters 3. Pump 4. Control valves 5.MOS sensor 6. Sensors' chamber and wood sample, 7. Arduino board, 8. Computer.

Table 1
The specifications of the sensors utilized in the olfactory machine.

Sensor	Main application	detection range (ppm)
MQ−3-S1	alcohol	0.05–10
MQ−135-S2	Air quality (ammonia, NOX, alcohol, benzene, smoke, carbon dioxide)	Alcohol 10–300 Benzene 10–1000
MQ−138-S3	Volatile organic compounds (aldehydes, alcohols, ketones and aromatic compounds)	5–500
TGS−2602-S4	Air pollutants (VOCs and aromatic gases)	1–30
TGS−2610-S5	Propane and butane	1–25
TGS−2620-S6	Alcohol, organic gases	50–5000

PCA was used for dimensionality reduction, simplifying the dataset by reducing the number of features while preserving maximum variance and essential information. LDA as a supervised classification technique was used to distinguish between predefined classes based on the processed data, facilitating the accurate classification of samples.

3. Results and discussion

The linear discriminant analysis (LDA) in Fig. 3 shows four different classes of data in the olfactory machine system. Each class is marked with a different symbol. The results showed that this method could completely separate the control (untreated) and different thermally-modified woods. It also can be clearly seen that the four classes are well separated from each other, and only two classes, ThermoWood® and Termovuoto®, had some overlap. The ellipses around each cluster indicate the scatter of the data in each class. The figure revealed the effectiveness of LDA in separating and classifying the olfactory machine data.

As can be seen in Fig. 4, the olfactory machine caused a striking difference between the thermally modified wood products and the control (untreated) wood. There were also clear and distinctive differences among the thermally modified wood products. The score plot is

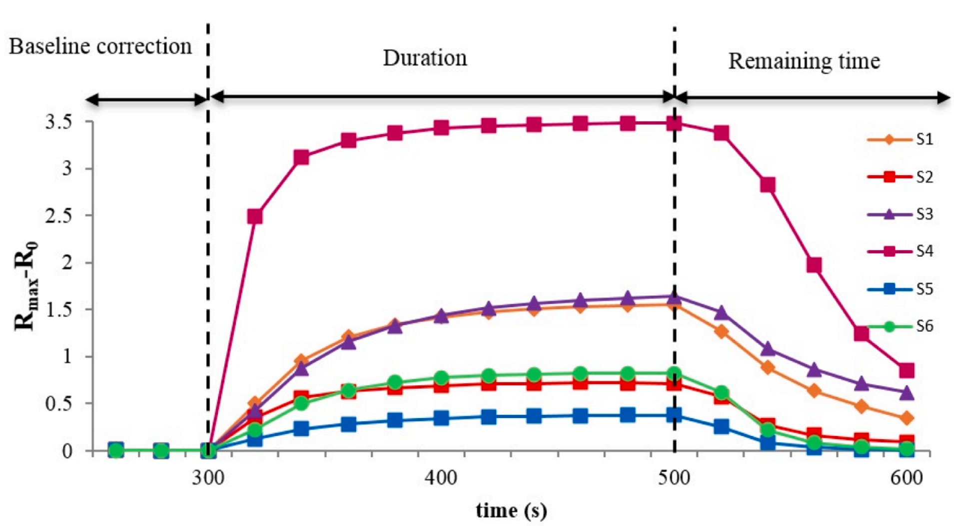

Fig. 2. Typical response of electronic nose sensors when analyzing wood samples.

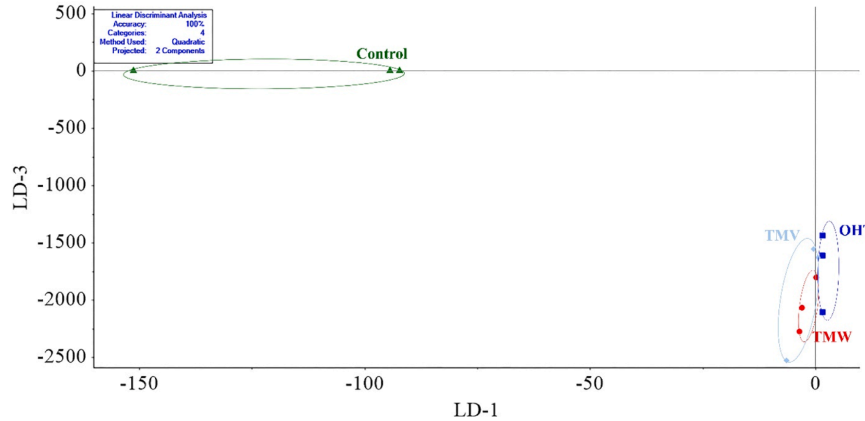

Fig. 3. The score plots for linear discriminant analysis (LDA) results from control and different thermally-modified woods; TMW: ThermoWood®, OHT: oil-heat treated wood and TMV: Termovuoto®.

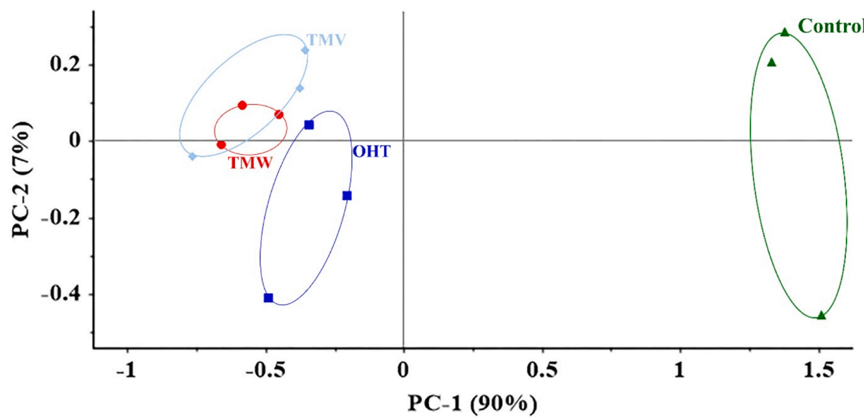

Fig. 4. Score plot principal component analysis (PCA) in the diagnosis of control and different thermally-modified woods; TMW: ThermoWood®, OHT: oil-heat treated wood and TMV: Termovuoto®.

characterized by two components: the first principal component (PC-1) accounts for 90 %, and the second principal component (PC-2) accounts for 7 %, explaining 97 % of the total data variance. These primary components (PC-1 and PC-2) capture the highest variance in the original dataset. In PCA analysis accompanied by a score plot, additional charts, such as a correlation loading plot, can also be generated [10]. The data from 4 categories are well separated from each other, while the data from 2 categories overlap. Nikoutadbir et al. (2024) found that the olfactory system and principal component analysis (PCA) effectively differentiated between two conifer species [23]. Lorenzo et al. (2024) also identified four types of wood products: Kamagong, Agoho, Acacia, and Sampalok, using YOLOv8 and Raspberry Pi 4B with an accuracy of 72.5 % [25]. In this study, the olfactory machine was able to accurately differentiate four types of thermally modified wood from untreated wood with 100 % accuracy.

Softwoods and hardwoods exhibit different VOC emission profiles. Softwoods primarily emit volatile terpenes, while hardwoods emit higher levels of hexanal, pentanal, and acetic acid [12,26]. Thermal treatment generally reduces terpene emissions in softwoods but increases acetic acid and furfural emissions in both wood types [12,26]. Thermally modified wood emits various VOCs that contribute to its odor profile. The primary compounds include aldehydes (e.g., hexanal, pentanal), acetic acid, furfural, and formaldehyde [27,28]. The odor profile changes significantly after thermal treatment due to the degradation of hemicelluloses and other wood components [12,26–28]. Electronic noses (e-noses) equipped with metal oxide sensors can effectively distinguish between different types of thermally modified wood based on their odor profiles. For instance, the PEN 3.5 e-nose was able to differentiate between untreated and thermally modified bamboo by detecting changes in terpenes, aromatic compounds, methane, and alcohols [22]. Similarly, an olfactory machine with six metal oxide semiconductors successfully identified specific odor profiles of *Picea abies* and *Pinus sylvestris* [23]. MOS sensors can detect and analyze the VOCs emitted during the thermal treatment of wood, which vary depending on the treatment method [10,23,29].

The correlation loading plot illustrates the strength of the correlation between the sensors and each of the primary components. In this visualization, a higher sensor loading on a principal component indicates a stronger correlation between that sensor and that component. A more significant loading on a principal component, which means it is closer to the outer ellipse, denotes a more significant influence of the sensor on distinguishing the classes based on that principal component compared to other olfactory sensors (Fig. 5). By representing the correlation loading of the sensors along the first principal component axis in this diagram, it can be observed that all sensors demonstrate a strong correlation with the first principal component, leading to the conclusion that the control wood significantly influences all sensors. Conversely, using various methods, the modified wood displayed the least influence on all sensors.

GC-O is used to identify and characterize odor-active compounds in wood. This technique involves the detection of VOCs and their corresponding odors, providing a detailed profile of the emitted substances [30,31]. It can identify key odorants and their intensities, which change significantly after thermal treatment [30]. Both e-nose and olfactometry

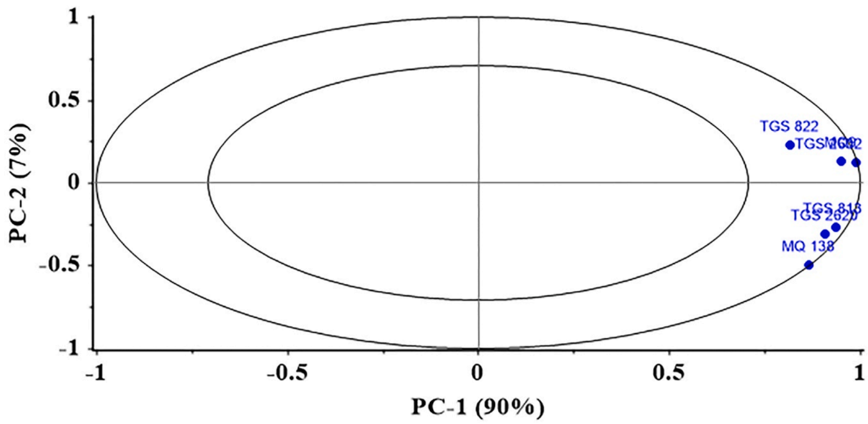

Fig. 5. Loading plot for principal component analysis in the diagnosis of control and thermally modified woods.

machines are valuable for identifying and classifying thermally modified wood. E-noses provide rapid and non-destructive analysis, making them suitable for real-time monitoring and quality control [22,32]. Olfactometry, combined with GC-MS, offers detailed chemical analysis and sensory evaluation, which is essential for understanding the impact of thermal treatment on wood odor [30,31].

4. Conclusion

Results obtained with the olfactory machine indicated that the amount of odor and VOCs in the various thermally modified wood products was different depending on the modification method. The highest amount of VOCs observed in the oil-heat treated wood may be due to stronger odors emitted by the chemical compounds of the oil. On the other hand, modification of wood in a steam environment (ThermoWood®) and especially under vacuum (Termovuoto®) usually leads to less odor because some VOCs are released during the modification process. Overall, our findings revealed that various thermally modified woods can be accurately detected and differentiated from one another, particularly in relation to control wood by using the olfactory machine equipped with different MOS sensors.

CRediT authorship contribution statement

Hadi Gholamiyan: Writing – review & editing, Supervision. **Seyed Saeid Mohtasebi:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Alireza Nikoutadbir:** Writing – review & editing, Visualization, Formal analysis, Data curation. **Hızır Volkan Görgün:** Writing – review & editing, Resources. **Mehrdad Nikjoo:** Writing – review & editing, Investigation, Formal analysis, Data curation. **tarmian asghar:** Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Öner Ünsal:** Writing – review & editing, Resources.

Declaration of Competing Interest

The authors declare no competing interests.

Acknowledgements

This research was conducted with financial support and laboratory facilities provided at College of Agriculture and Natural Resources, University of Tehran. The authors would like to acknowledge Mazand-Choob Arya Co. and Wood Preservers of Persia© Co. for providing the thermally-modified woods.

Data availability

Data will be made available on request.

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