Applying TOPSIS Algorithm for Odour Classification Model

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***Abstract*—Odour classification is a complex task with significant implications across various industries in Industrial Evolution 4.0 (IR4.0), including food and beverage, environmental monitoring, and perfumery. Traditional methods often struggle with subjectivity and the multidimensional nature of odour data. This paper introduces an approach by applying the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) algorithm for odour classification. TOPSIS, a widely-used as multi-criteria decision-making (MCDM) method, ranks alternatives based on their proximity to an ideal solution, effectively handling both qualitative and quantitative data. In this study, we outline the integration of TOPSIS for odour classification that can be applied in application for future. Simulation datasets comprising sensory evaluations were utilised to validate the approach. The idea is the highest ranking, the closeness of testing data to the model trained. The results demonstrate that the TOPSIS-based classification method proved can be applied for odour classification. By systematically evaluating multiple criteria influencing odour perception, our approach offers a robust, reliable, and efficient solution for odour classification challenges.**

Keywords— TOPSIS Algorithm, Odour Classification, Classification Model, Multi-Criteria Decision Making (MCDM), Sensor Technology

I. INTRODUCTION

Odour classification is a vital process with significant implications for various industries, including food and beverage, environmental monitoring, and perfumery. Over the past two decades, substantial progress has been made in understanding the mechanisms of odour perception and in developing techniques for odour classification. However, traditional methods often suffer from issues such as subjectivity, variability in human sensory evaluations, and the complexity of odour data, which encompasses both qualitative and quantitative elements [1], [2].

Conventional approaches to odour classification typically rely on sensory panels, where human subjects evaluate odours based on predefined criteria. While valuable, this method is limited by subjective bias, variability in perception, and high costs associated with extensive sensory evaluations. Additionally, chemical analysis techniques like gas provide objective data but are often complex, expensive, and require specialised equipment [3], [4].

A typical odour classification system relies on an array of sensors known as an electronic nose (e-nose). These sensors mimic the human olfactory system by detecting volatile organic compounds (VOCs) in the environment. The signals generated by the sensors are then processed using various algorithms to classify the odours. The challenge in odour classification lies in the complexity and variability of odour signals, which can be influenced by numerous factors including temperature, humidity, and the presence of multiple odourants [5].

Odours originate from a variety of sources, each producing a unique combination of chemical compounds. In the food industry, odour classification can help in assessing the freshness and quality of products by detecting spoilage or contamination. In healthcare, it can aid in diagnosing certain medical conditions, as diseases such as diabetes and infections often emit characteristic smells. Environmental monitoring uses odour detection to identify pollution levels, track air quality, and detect hazardous substances. In security, odour classification is employed in the detection of explosives and narcotics [6].

Odours are typically composed of complex mixtures of volatile organic compounds (VOCs). Each odour can consist of dozens to hundreds of different chemical components, each contributing to the overall scent profile. This complexity makes it difficult to isolate and identify individual components accurately. Odour signals can vary significantly depending on environmental conditions such as temperature, humidity, and airflow. These factors can influence the concentration and distribution of VOCs, leading to fluctuations in sensor readings. This variability poses a challenge for maintaining consistent and reliable odour classification [7].

Processing raw sensor data to extract meaningful features is a critical step in odour classification. This involves techniques such as signal filtering, normalisation, and dimensionality reduction. The challenge lies in selecting appropriate preprocessing methods that preserve relevant information while minimising noise and variability. Many odour classification applications demand real-time processing and portable solutions. Achieving real-time performance requires efficient algorithms and fast sensor response times. Portability involves challenges related to miniaturization, power consumption, and ensuring consistent performance in different environments [8], [9].

One such way to classify the odour is the TOPSIS, which has been extensively used in areas such as environmental management, engineering, and healthcare due to its ability to rank alternatives based on their proximity to an ideal solution. The application of the TOPSIS algorithm in odour classification models can enhance the accuracy and robustness of these systems. By systematically evaluating the sensor data and providing a clear ranking of potential odour classes, TOPSIS helps in making informed decisions in real-time applications. This method is particularly valuable in environments where rapid and reliable odour detection is crucial [10].

Recent studies have highlighted the efficacy of the TOPSIS algorithm in various applications, including odour classification and sensor optimisation for electronic noses. For example, an integrated evaluation model combining TOPSIS with the entropy weight method (EWM) was proposed to optimise sensor arrays based on multiple criteria, significantly enhancing the performance of electronic noses in odour detection and classification. Another study demonstrated the application of the OWSum algorithm to predict specific odours of molecules based on their structural patterns, emphasising the importance of accurate odour prediction models in various fields [5].

This paper presents an approach to odour classification by applying the TOPSIS algorithm. By leveraging the strengths of TOPSIS in handling multidimensional data and reducing subjective bias, we aim to develop a more robust and reliable odour classification system. The methodology involves the systematic selection of criteria that influence odour perception, the application of the TOPSIS algorithm to rank odours based on these criteria, and validation using comprehensive datasets that include both sensory evaluations and chemical analyses.

The rest of this paper is structured as follows: Section II is the related work regarding the TOPSIS algorithm. Section III provide a methodology for the proposed TOPSIS algorithm for Odour classification. Section IV is the simulation to prove the TOPSIS model for classification odour. Section V is conclusion and future work.

II. Related Work

The TOPSIS algorithm has been by Hwang and Yoon for the first time in 1981, aiming to select the alternatives having the furthest distance from the negative ideal solution and the shortest distance from the positive ideal solution simultaneously [10]. Nowdays, TOPSIS has been widely applied in various domains to solve multi-criteria decision-making problems. Its application in sensor data analysis is particularly noteworthy, as it can effectively handle complex datasets and provide robust decision-making capabilities [10], [11].

TOPSIS algorithm has been applied in various sensor-related applications to improve decision-making and classification performance. In odour classification, however, its use remains relatively unexplored. Previous studies have successfully employed TOPSIS in other sensor applications, such as air quality monitoring and gas detection, demonstrating its potential to enhance classification accuracy and robustness using Fuzzy. This research aims to fill the gap by integrating TOPSIS into odour classification models and evaluating its effectiveness [12], [13].

The research from Ying Jie Zhu *et. al*, utilises the entropy weight method, TOPSIS, and RSR model to evaluate the quality of graduate students at Changchun University. The study aims to address the quality evaluation of graduate students, focussing on majors like literature, law, and economics. The compared algorithms in the research are the TOPSIS and RSR methods for student source quality evaluation. The results show that the quality of students in literature, law, and economics at Changchun University is relatively high. Future work may involve further refining the evaluation models and applying them to other majors for comprehensive quality assessment [11].

Different from Li *et. al*, the research paper focusses on a decision-making model for forest species using the entropy weight method and the TOPSIS model. The problem addressed is maximising forest carbon sequestration without harming the environment, considering various factors like economy, ecological balance, and climate. The compared algorithm is the TOPSIS method, which is a multi-objective decision-making method widely used in evaluation. The research results in a practical model that can be adapted to different forest types and local preferences, providing a solution with strong carbon sequestration capabilities. Future work involves applying the model to different forests, collecting data, and making recommendations based on the model's predictions [13].

Next, the research paper from Yijun Yao *et. al* focusses on the performance evaluation of logistics listed enterprises using the Entropy weight TOPSIS method. The algorithm used in the research is the Entropy weight TOPSIS method, which combines the entropy weight method and TOPSIS method to evaluate the business performance of enterprises. The problem addressed is the unbalanced development of logistics enterprises and the need for improvement in business performance. The research compares various evaluation methods used for logistics enterprise performance, such as DEA, Malmquist index, grey correlation analysis, and TOPSIS. The results of the research show that high-performance enterprises excel in profitability, solvency, and operation ability, while medium-performance enterprises lack in profitability, debt paying ability, and innovation ability. Low-performance enterprises struggle across all dimensions of capability. Future work could involve further refining the evaluation model, exploring additional factors influencing business performance, and extending the analysis to a broader range of logistics enterprises [14].

From Yao *et. al*, the problem addressed in the research is the selection of sustainable suppliers, considering economic sustainability factors as the most important criteria, followed by social sustainability factors. The study compares integrated compensatory (Fuzzy TOPSIS) and non-compensatory (improved ELECTRE) decision methods used for supplier selection in the context of sustainable supplier selection. The results of the research involve the development of a framework that provides a method for selecting sustainable suppliers in the automobile industry, emphasising economic and social sustainability factors. Future work in this area could involve further refining the framework, exploring additional criteria for sustainable supplier selection, and potentially expanding the application of the fuzzy-AHP-TOPSIS method to other industries beyond the automobile sector [12].

The researcher from Zhang *et. al* applied the entropy weight TOPSIS method to evaluate the performance of different foam extinguishing agents for transformer oil fires. The problem addressed was the variability in the effectiveness of foam extinguishing agents in suppressing transformer oil fires under different conditions. The compared algorithms were the different types of foam extinguishing agents evaluated in the study. The research results indicated that fluoroprotein foam was the most effective overall in suppressing transformer oil fires. Future work could involve further optimising the evaluation index system and exploring additional foam extinguishing agents for transformer oil fires [15]. Next subsection will discuss in detail how the TOPSIS algorithm can be modelled as a classification.

III. Methodology

To develop an effective classification model using the TOPSIS algorithm, we constructed a methodology comprising the following steps: sensor data collection, data training, feature extraction for modelling application of the TOPSIS algorithm, and evaluating the data based on the classification TOPSIS model.

A. Sensor data collection

A system equipped with an array of sensors is used to detect volatile organic compounds (VOCs) from various odour sources. The suitable application is applied to the microcontroller for gathering the data for the future. The sensor array typically includes metal oxide sensors (MOS), conducting polymer sensors, and quartz crystal microbalance (QCM) sensors, chosen for their sensitivity and selectivity to different VOCs.

B. Data training for Classification Model

The system is exposed to different odour profiles under controlled environmental conditions to ensure consistent data collection. Sensor responses are recorded over a specified period for 120 seconds, capturing the dynamic changes in sensor signals as they interact with the odour ants. Multiple readings are taken for each odour profile to account for variability and ensure reliable data. Odour sensor will be in a numbering of bits from 0 until 255. Thus, the sensor signals will be averaged to a common scale to ensure comparability between different sensors and samples.

For each new odour profile, the training of average data steps is applied to form a model. The TOPSIS algorithm needs a model to produce the result of the highest rank and the lowest rank by calculating the distances of the new sample to the ideal and negative-ideal solutions. Extracted features from the preprocessed sensor data (120 seconds) are treated as criteria for the TOPSIS algorithm. Key statistical, dynamic, and frequency-domain features are included to comprehensively represent each sensor responses to different odours. The formula for normalising each data sensor for data training is using *Average Sense Data* as in (1):

$$Average\ Sense\ Data = \frac{Total\ of\ 120\ data}{120} \tag{1}$$

In the formula, *Total of 120* data is the data that senses for 120 times. The total of 120 data will be divided by 120 data to get the average number. Each data sensor will produce average data which can be the model for the TOPSIS algorithm used to find the ideal solution later. From this data training, the model of the averaged data will be stored in the memory as the reference data in the TOPSIS algorithm. This stored model serves as the reference for comparing the odour samples at least 3 models in the memory. This is because the TOPSIS algorithm needs to rank the senses based on the model. Figure 1 shows the process.

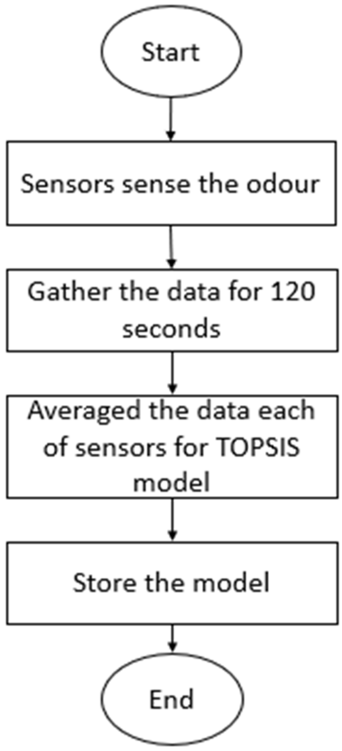

Fig. 1. Process of data collection and training of data

C. Evaluate the sample using TOPSIS

In the TOPSIS algorithm for odour classification, the traditional TOPSIS applied. A decision matrix is created where each row represents an odour sample and each column represents a feature. This matrix forms the basis for the TOPSIS analysis. The decision matrix will be normalised to ensure that all features are on a comparable scale, which is essential for the TOPSIS algorithm to function correctly.

Then, the weights are assigned to each feature based on their importance in differentiating between odour classes. This step can be guided by domain knowledge or statistical methods such as entropy weighting.

The ideal solution (positive ideal) is determined by selecting the best feature values from the normalised decision matrix. These values represent the optimal sensor responses for each feature. The negative-ideal solution (negative ideal) is determined by selecting the worst feature values from the normalised decision matrix. These values represent the least desirable sensor responses for each feature. The Euclidean distance from each odour sample to both the ideal and negative-ideal solutions is calculated. This step quantifies how close each sample is to the optimal and least optimal sensor responses.

The relative closeness of each odour sample to the ideal solution is computed, which forms the basis for ranking the samples. The formula for relative closeness as in (2):

$$Relative\ Closeness, C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{2}$$

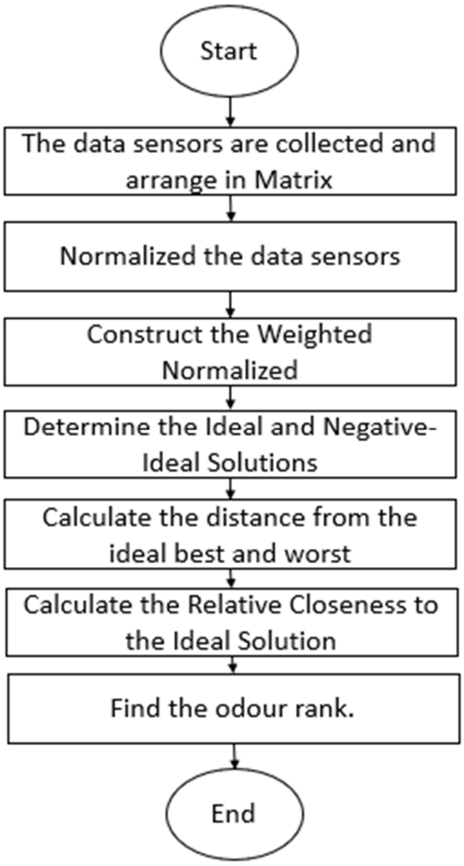

Fig. 2. TOPSIS algorithm for Odour Classification

The relative closeness of each odour sample to the ideal solution is computed, which forms the basis for ranking the samples. S_i^+ is the distance to the positive ideal solution and S_i^- is the distance to the negative ideal solution.

The classification model is validated using techniques such as cross-validation to ensure its accuracy and robustness. By creating a comprehensive model for odour classification using the TOPSIS algorithm, we leverage the strengths of multi-criteria decision-making to handle complex sensor data. The detailed process of model creation, from data training to model storage and utilisation, ensures that the classification system is robust, accurate, and capable of handling real-world odour detection scenarios. Figure 2 shows the flow of the TOPSIS algorithm for odour classification.

IV. Simulation and Discussion

A. Setup Parameter

To evaluate the approach, we simulated the TOPSIS algorithm using the random data produced by Matlab. First step, three (3) models of data training from random numbering provided by Matlab as a sample. In simulation, 120 data will be generated and calculate the average using Eq. (1). Table 1 shows the parameters of the TOPSIS algorithm for simulation.

TABLE I. Parameter of Average Sample Simulation

Model Training	Sensor1	Sensor2	Sensor3	Sensor4	Sensor 5
A	224	234	123	111	23
B	229	10	133	122	10
C	144	34	13	111	254

Second step, is to test the odour sense by collecting 120 seconds of data. Then the same step is to calculate the average of the data using (1). This step is to get the similar data as the model to be evaluated by the TOPSIS algorithm. The weight setup is 0.2, represents a scenario where all criteria are considered equally important. Adjusting weights according to the actual importance of each criterion will make the TOPSIS analysis more reflective of the real-world preferences and priorities. The Table II shows, the test data was generated randomly to compare with the model that will be discussed in Section B.

TABLE II. Parameter of Test Simulation

Sample Test	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5
Test data	245	230	120	90	20

In Sub-section *D*, we will discuss the percentage of similarities between test data and the model to find out the exact model that is very close to the test data. The similarities of data will be used in (3). Data Test is the value of the data collected and Data Model is the model data that has been trained.

$$Similarities = \frac{Smaller\ Value}{Larger\ Value} X\ 100 \tag{3}$$

B. Result and Discussion

In this section, we will show all the steps of TOPSIS for odour classification. Table III shows the data of normalisation data sensors taken from Table I.

TABLE III. NORMALIZATION OF DATA SENSORS

Model Training	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5
A	0.6469	0.6204	0.3261	0.2943	0.061
B	0.5422	0.0237	0.7884	0.2888	0.0237
C	0.691	0.2061	0.0788	0.6728	0.1455

TABLE IV. WEIGHTED NORMALIZED

Model Training	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5
A	0.1294	0.1241	0.0652	0.0589	0.0122
B	0.1084	0.0047	0.1577	0.0578	0.0047
C	0.1382	0.0412	0.0158	0.1346	0.0291

TABLE V. BEST SOLUTION

	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5
Ideal Solution	0.1382	0.1241	0.1577	0.1346	0.0291

TABLE VI. WORST SOLUTION

	Sensor1	Sensor2	Sensor3	Sensor4	Sensor5
Worst Solution	0.1084	0.0047	0.0158	0.0578	0.0047

TABLE VII. DISTANCE IDEAL AND BEST

Model	Distance Ideal Best	Distance Ideal Worst
A	0.121	0.1311
B	0.147	0.1419
C	0.1643	0.0933

TABLE VIII. CLOSENESS RESULT

Model	Closeness Result
A	**0.52**
B	0.4911
C	0.3622

Higher closeness score indicates the model is closer to the ideal solution and further from the worst solution. However, the closeness score indicates the model is further from the ideal solution and closer to the worst solution. Model A has the highest closeness score of 0.52, which means it is the closest to the ideal solution and farthest from the worst solution among the models.

Model C has the lowest closeness score of 0.3622, meaning it is the farthest from the ideal solution and closest to the worst solution. Therefore, model A is considered the best option because it has the highest closeness score, indicating it is the nearest to the ideal solution according to the TOPSIS method.

C. Sensor Pattern

Figure 3 illustrates the odour sensor pattern across five sensors, labelled Sensor 1 to Sensor 5. The y-axis represents the value of the sensors, ranging from 0 to 250. Four different patterns, labelled of model A, B, C, and Test data, were displayed.

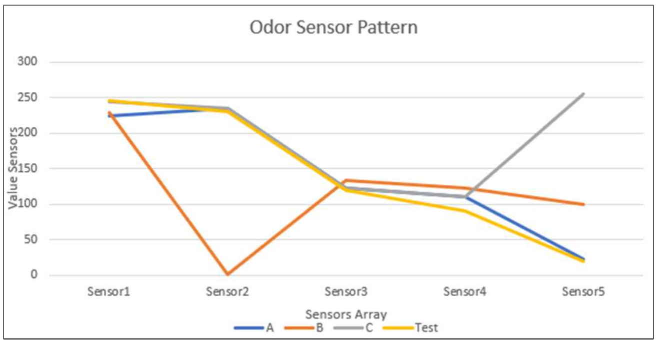

Fig. 3. TOPSIS algorithm for Odour Classification

The classify model shows the sensor values decrease from Sensor 1 to Sensor 5 which is Model A. Test data shows a relatively stable response across the sensors same like model A. Pattern B demonstrates a sharp decline from Sensor 1 to Sensor 2, followed by a gradual increase. Pattern C exhibits a steady decrease, with a slight increase at Sensor 5.

The pattern shows the test data pattern is more likely the Model A. This proves from the TOPSIS algorithm that rank model A is the closeness to the test data. TOPSIS algorithm shows that the highest rank can be a classification method for the multiple models.

D. Similirities of Sensor

This subsection is to calculate the percentage of similarities of the test data to the models. The test data will use the Equation (3).

TABLE IX. PERCENTAGE OF SIMILARITIES

Sample Training	Percentage of Similarities to Test Data (%)					
	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Average
A	91.43	98.29	97.56	81.08	86.96	**91.06**
B	93.47	0.43	90.23	73.77	20	55.98
C	99.59	98.29	97.56	81.08	7.87	76.88

Based on the Table IX, the percentage closeness calculation helps determine how similar the test data is to each of the model data sets (A, B, and C) based on the values recorded by the sensors. The calculation was done for each sensor and then averaged to get an overall closeness percentage for each sample.

Model A shows a high degree of similarity across most sensors. The closeness is consistently high, especially for Sensor2 and Sensor3, indicating that Model A is the most similar to the test data overall.

Model B has a low overall similarity to the test data, primarily due to Sensor2 and Sensor5, which show very low closeness percentages. Sensor2's value of 1 is especially divergent from the test data's value of 230, drastically lowering the overall closeness percentage.

Model C shows high similarity in most sensors except for Sensor5, which has a very low closeness percentage. This low value for Sensor5 significantly reduces the overall average closeness. If Sensor5 were excluded, Sample C would be highly similar to the test data. Thus, based on these calculations, Model A is the best match for the test data, indicating that the test data is most similar to Model A among the three samples. The result is the same as the TOPSIS calculation which is model A is the first in rank.

V. Conclusion and Future Work

TOPSIS algorithm proved can be used for odour classification. By applying this algorithm, the odour pattern can be ranked from the highest and to the lowest. The highest rank is the closeness to the model. The model was trained with the average for the comparison of different datasets. The TOPSIS algorithm ranked model A is the highest or the closest to the test data. Then, the data was illustrated with the line graph to figure out the pattern of the test data and model. The test data shows very close to model A. The test data also proved the similarities of model A is at 91.06% compared to the other models. The emerging technology of Industrial Revolution 4.0, became the classification technology is crucial things for the future.

For the future work, this method can be applied to the real application and trained with more than 3 models. The simulation of the traditional TOPSIS algorithm already proved can be classified the odour pattern. For future, more sensors can be applied to get more robust.

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