

Real-Time Methanol Detection in Distilled Spirits via BME688 MOX Sensor Array and Machine Learning

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Abstract

Methanol contamination in distilled beverages remains a serious public health risk, particularly in the context of illicit or poorly controlled production. Although confirmatory determination of methanol is routinely performed using laboratory-based techniques such as gas chromatography, spectrophotometry, and enzymatic assays, these approaches are often impractical for rapid screening due to infrastructure, expertise, time, and cost constraints. This study proposes a portable, fast and low-cost scanning framework that integrates the Bosch BME688 metal-oxide (MOX) sensor array with machine-learning models to detect methanol-related patterns in mixtures at varying ratios. Measurements in experiments were conducted on controlled ethanol-methanol mixtures and extended to real beverage matrices (Raki- and Whisky-based samples) to better reflect practical conditions where matrix effects may confound detection. After generating the raw dataset, the first preprocessing step involved denoising the multi-sensor, multi-step heater signals. The data were temporally aligned, a logarithmic transformation was applied, and standardisation was ensured. Models have been constructed using multiple heater profiles and a series of classification and regression algorithms to evaluate both categorical discrimination and quantitative prediction capabilities. The results demonstrate that MOX sensor responses, when paired with appropriate preprocessing and learning models, provide a viable basis for rapid, in-situ methanol screening in distilled beverages, supporting early warning and prioritisation prior to confirmatory laboratory analysis. Further studies are planned to expand the range of commercially consumed beverages and to evaluate the study's generalizability and limitations beyond controlled laboratory settings.

1. INTRODUCTION

Alcoholic beverages have a large consumer base worldwide and are an established component of daily life, social interaction, and cultural habits in many societies [1], [2], [3], [4]. However, distilled alcoholic beverages are known to contain methanol, generally due to improper production conditions [5]. This highly toxic compound can cause serious health problems, including acute intoxication, irreversible vision loss, multiple organ damage, severe central nervous system effects, and death [6], [7]. The presence of methanol in potable alcohol is typically associated with uncontrolled or poorly managed production processes, such as improper fermentation, inadequate distillation control, or contamination [8].

Today, methanol determination in distilled alcohol is primarily achieved using traditional laboratory-based analytical methods. These methods mainly include gas chromatography [9], colorimetric–spectrophotometric [10], and enzymatic approaches [11]. These techniques offer high sensitivity, accuracy, and analytical reliability and are therefore used as reference methods for methanol verification. However, their reliance on specialised equipment, trained personnel, and laboratory infrastructure limits their practicality for rapid, on-site, and mobile screening applications.

Given the operational limitations of current analytical methods, a complementary screening layer is needed to enable rapid, cost-effective, and expert-independent detection of methanol under production and field conditions. This approach should not completely replace confirmatory laboratory methods but rather serve as a screening layer for early warning and preliminary risk assessment. Such an early-warning layer can support timely intervention and decision-making by enabling rapid identification of potential risks, prioritising suspicious samples for confirmatory analysis, and improving resource utilisation.

In this context, the present study aims to develop a real-time methanol screening framework for distilled alcoholic beverages by integrating a Bosch BME688 metal-oxide (MOX) gas sensor [12] array with machine-learning and regression models. The proposed approach seeks to exploit methanol-related volatile patterns to enable effective classification and quantitative estimation under controlled measurement conditions. The results demonstrate the potential of this framework as a portable and cost-effective screening tool that can be integrated into production monitoring and field inspection workflows, while laying the groundwork for future validation and broader generalisation studies.

2. RELATED WORKS

The determination of methanol in distilled alcoholic beverages remains reliant mainly on traditional laboratory analytical methods. Among these methods, gas chromatography (GC), particularly GC-FID and GC-MS configurations, is considered a reference method due to its high sensitivity and selectivity [13]. Widely used in regulatory and validation analyses, these techniques allow for the quantitative and reliable determination of methanol. In addition to gas chromatography, spectrophotometric approaches, particularly methods based on chromotropic acid-based colourimetric reactions, have been reported in the literature for methanol determination [14]. These methods involve measuring the absorbance of the coloured complex formed by the chemical conversion of methanol, thereby providing a quantitative evaluation.

Furthermore, enzymatic methods have been reported in the literature; these approaches generally rely on the enzymatic conversion of methanol via enzymes such as alcohol oxidase or methanol dehydrogenase [15]. Although these classical methods offer high analytical accuracy and reproducibility, they are not well suited to rapid, on-site, or mobile applications due to their need for controlled laboratory environments, specialised equipment, and expert personnel. This constitutes a significant disadvantage, particularly in situations that require timely risk assessment during field inspections and production phases.

To address this gap in the literature and applications, in recent years, a significant portion of studies on rapid methanol screening have focused on gas sensors (electronic noses) and pattern-recognition-based approaches [16]. These systems aim not at the direct and selective measurement of a single analyte, but rather at classifying or quantitatively predicting the multivariate response patterns generated by volatile components in the sample's headspace using different sensor systems. Therefore, machine learning

methods such as Support Vector Machine, Random Forest, k-NN, and Artificial Neural Networks are widely used to interpret sensor responses, enabling inference of targets such as methanol presence/level from multiple sensor signals[17], [18]. In this context, metal-oxide (MOX) sensors, in particular, are attracting attention for field-oriented applications due to their advantages, including low cost, rapid response, and portability[19].

While these sensor- and AI-based approaches are promising for methanol screening, significant limitations remain in the literature. Firstly, many studies evaluate pure alcohols under controlled, idealised conditions. Although product-specific aroma components in distilled beverage matrices can significantly shape the VOC profile, this effect is often insufficiently accounted for in modelling and evaluation. Furthermore, some approaches focus solely on classification, while quantitative estimation of methanol levels and practical measurement protocols suitable for real-time field scenarios are not always considered together.

In this study, the Bosch BME688 sensor matrix, widely used in similar applications and featuring an integrated MOX sensor platform, was employed to monitor environmental volatile profiles. Measurements were not limited to pure ethanol-methanol mixtures; they were also performed on samples of raki and whiskey, distilled beverage matrices that are considered critical in terms of methanol risk in the market and frequently addressed in quality control. The sensor data obtained in this study were evaluated using classification models to differentiate methanol levels and regression analyses to quantify methanol content. Considering these aspects, this study aims to provide a practical framework that meets the requirements of realistic matrices and quantitative estimation in sensor-based methanol screening.

3. MATERIALS AND METHODS

3.1. BME 688 sensor, specification, and capabilities

In this study, which aims to determine methanol content in distilled alcoholic beverages, headspace VOC measurements of the samples were performed using a Bosch BME688 sensor. The Bosch BME688 is a miniaturised, multi-parameter environmental sensor that integrates a metal-oxide-semiconductor-based gas-sensing element with temperature, relative humidity, and barometric pressure sensors in a single package.

The BME688 sensor was considered not as a detector that directly and selectively measures a single compound, but rather as a chemical-fingerprint transducer that produces a reproducible response pattern to the VOC mixture originating from the distilled-beverage matrix. In addition, owing to its small size, low power consumption, and capability to generate high-sampling-rate time-series signals under controllable heater programs, the sensor offers practical advantages for rapid screening-oriented sensing platforms.

3.2. Usage Areas of the BME 688 sensor

The BME688 sensor's ability to provide sensitive measurements and respond to a broad spectrum of volatile compounds supports its use across diverse application areas. Accordingly, it can be customised for domains where environmental parameters, particularly temperature, humidity, and VOC-related signals, are critical. In the present study, this versatility was leveraged to adapt the BME688 for analysis of distilled alcoholic beverages, aiming to capture reproducible response patterns from complex VOC backgrounds and to improve the discrimination and quantitative estimation of methanol in the presence of matrix-derived volatiles.

Recently, the BME688 sensor has been used in numerous application scenarios in the literature. The most common scenarios include indoor and outdoor air quality monitoring [20], [21], food freshness assessment [22], [23], and food adulteration detection [24], [25]. Additionally, safety-focused scenarios include early fire detection in forestry and agricultural areas [26], anomaly detection in critical areas and laboratory environments [27], early detection of environmental risks in military facilities and field conditions [28], bad-smell [29] and leak-detection monitoring [29]. Furthermore, it has been observed in areas such as disease diagnosis, monitoring [30], and microbial activity detection [30]. Moreover, the sensor has shown potential for use in other applications involving Volatile Organic Compounds (VOCs), volatile sulphur compounds (VSCs), and other gases such as carbon monoxide and hydrogen.

3.3. Sensor Matrix and Sensor Matrix Configuration

Instead of using a single sensor to measure environmental conditions and detect methanol in the mixture, a matrix of 8 BME688 sensors was employed. There are many uncontrollable parameters affecting the measurement environment. Therefore, recreating the exact same experimental conditions at different times is unrealistic. For this reason, using multiple sensors simultaneously is crucial for testing different profile settings in the same experimental environment. Furthermore, increasing the volume of data collected per unit time also improves the accuracy of artificial intelligence models. Figure 1 shows the BME688 gas sensor matrix used for multi-environment measurements in this study.

There are two important configurations that determine the sensor's measurement capabilities and affect the characteristics of the generated dataset. The first is the Real Duty Cycle (RDC) profile, which governs the sensor's scanning and sleep cycles. The RDC profile can save up to 80% of power, particularly in scenarios where sensor nodes are externally powered and far from the city grid, thereby extending their lifespan. Figure 2 shows some RDC profiles that can be configured for BME 688 sensors in different application scenarios.

In this study, because the sensor nodes were powered by the city grid and artificial intelligence models required collecting more data per unit time to make more stable decisions, the nodes were never put to sleep during data collection. The nodes were operated in continuous scanning mode using the RDC1-0 profile.

Another parameter that determines the sensor's operating status is the Heater Profile (HP). In metal oxide semiconductor (MOS) sensors, gas interaction occurs on the sensor surface. VOC molecules

adhere to (adsorption) or detach (desorption) from the sensor surface. Increasing or decreasing the sensor's operating temperature (temperature modulation) alters the relative rates and balance of these two processes. In MOS sensors, modulation of the operating temperature significantly affects the dynamic character of the sensor response by altering the VOC adsorption-desorption kinetics and surface reactions on the sensor surface.

In this study, four distinct temperature modulations were applied simultaneously to eight sensors. This enabled identification of the HP profiles most effective for detecting methanol in potable alcohol. Figure 3 shows the temperature modulations used in this study (HP-301, HP-354, HP-413, HP-503).

The 8 sensors in the sensor matrix are grouped in pairs, and each pair is configured with a different HP profile. Figure 4 shows which HPs are configured for each sensor pair in the matrix.

This strategy enables simultaneous measurements of 4 different HPs in the same experimental setup and verifies the electrical resistance measured by one sensor against another loaded with the same HP.

3.4. Experimental Setup

In this study, data were collected in three stages. In the first stage, a measurement setup was prepared to test the sensor's capability to detect pure alcohol, excluding product-specific odour and aroma effects of commonly consumed alcoholic beverages. The experimental setup, prepared from ethanol-methanol mixtures, is shown in Fig. 5.

There is no standard value for dangerous methanol levels in potable alcohol [32]. While some limit values are reported in the literature, these can vary from person to person [33], [34]. Consequently, because this study is primarily an analytical screening and classification study rather than a chemical dose study, methanol concentrations well below the legally hazardous limits were used to test sensor and machine-learning capabilities. The classes were created considering this conceptual framework.

To enable the sensor to recognise VOC fingerprints in alcohol, samples were prepared by mixing commercially available ethanol (Eth) and methanol (Met) in different ratios. A total of 6 mixture samples, prepared at different ratios, were left at room temperature for a while to allow homogenisation. The mixture samples used for measurement were prepared as follows: 1. Mixture 100% Eth. – 0% Met., 2. Mixture 97.5% Eth. – 2.5% Met., 3. Mixture 95% Eth. – 5% Met., 4. Mixture 90% Eth. – 10% Met., 5. Mixture 80% Eth. – 20% Met., and 6. Mixture 50% Eth. – 50% Met. In all samples, the total volume of the mixture was set at 200 ml.

After placing the 6 mixtures into different Erlenmeyer flasks, measurements began on 12.05.2025 at 09:00 and ended at approximately 15:00. Sensor Matrix 0 was used only to measure the samples in the flasks, while Sensor Matrix 1 was used to measure the empty flask. The sensors were operated at room temperature for approximately one hour to allow them to stabilise.

After the sensors stabilised, Sensor Matrix 0 was positioned in the first Erlenmeyer flask and measurements were taken for 30 minutes. After each sample measurement, to allow any remaining VOCs from the previous sample to dissolve on the sensor membranes, the sensors were allowed to measure at room temperature for 20 minutes. Subsequently, measurements were taken from each bottle for the same duration, using the same procedures.

In the second phase of the data collection process, similar experimental mixtures were used, this time with Raki, a commercially consumed alcoholic beverage in Turkey. This data collection process began on December 22, 2025, at 09:00 and ended at approximately 14:00. Data were collected using the same measurement procedures as in the previous phase. The experimental setup prepared from mixtures of raki, water, ethanol, and methanol is shown in Fig. 6.

Many commercially sold Raki have an alcohol content between 40% and 50% [35], [36], [37]. To maintain the alcohol content, five grades were created by mixing ethanol, methanol, and pure water in varying proportions with 100 ml of pure raki.

The mixture samples used for measurement were prepared as follows: 1. Mixture 100 ml raki – 55 ml water – 45 ml Eth. – 0 ml Met., 2. Mixture: 100 ml raki – 55 ml water – 42 ml Eth. – 3 ml Met., 3. Mixture 100 ml raki – 55 ml water – 37 ml Eth. – 8 ml Met., 4. Mixture 100 ml raki – 55 ml water – 35 ml Eth. – 10 ml Met., and 5. Mixture 100 ml raki – 55 ml water – 30 ml Eth. – 15 ml Met..

The third phase of the data collection process was carried out with whiskey, another commonly consumed distilled alcohol frequently associated with methanol poisoning cases worldwide. The experimental setup, prepared from mixtures of whisky, water, ethanol, and methanol, is shown in Fig. 7.

All the mixtures used in the raki samples were applied to the Whiskey in the same proportions. Data collection, initiated with 5 samples created using different ratios of Whiskey, water, ethanol, and methanol, was conducted on December 24, 2025. Data collection began at 09:00 and continued until approximately 14:00.

4. MODEL SELECTION

After data collection was complete and datasets were created, the data were pre-processed to improve the performance of regression and classification models. Once the data were ready for use, they were subjected to regression and classification algorithms commonly used in the literature, and the results were compared.

4.1. Raw Data and Dataset

As a result of the data collection process, three independent datasets were created: Alcohol, Raki, and Whisky datasets. Figure 8 shows the raw data from sensor number 3 in the Alcohol dataset of the sensor matrix. The classifications in this dataset are labelled by the ethanol concentration in the mixture.

As shown in Fig. 8, as the methanol concentration in the mixture increases, the gas composition's resistance in the environment increases. If an imaginary vertical line is assumed from any point on the graph in Fig. 8, it can be said that this line forms a unique fingerprint of that moment on the time axis. The alcohol dataset comprises 8.812 data cycles. Each data cycle contains 10 data points. Therefore, this dataset comprises 88.120 data points.

The graph shows that the classes are evenly distributed in the dataset, ensuring proportional representation when building regression and classification models. The other datasets, Raki and Whisky, contain 7.851 and 8.306 data cycles, respectively. This corresponds to 78.510 and 83.060 data points, respectively. Figure 9 shows the classes in the Raki and Whisky datasets, along with the raw data collected by sensor 1 in the Raki dataset and sensor 7 in the Whisky dataset.

The names of the classes in the Raki and Whiskey datasets are derived from the millilitre-level values of the methanol content in the mixture. As shown in Fig. 9, as in the Alcohol dataset, a positive correlation is observed between methanol in the mixture and the electrical resistance of the gas mixture measured by the sensors in both datasets.

4.2. Data Preprocessing

In this study, the output of the MOX sensors used as ambient measurements reflects the total electrical resistance of the VOCs in the mixture, rather than being specific to a single gas type. Therefore, in this study, which was conducted to detect the presence and level of methanol in drinkable alcohol, ethanol, which is dominant in distilled beverages, and product-specific aroma components can mask the methanol signal. Consequently, in the literature, preprocessing sensor data is widely recognised as a critical requirement for model performance and generalizability.

The gas sensor matrix data is saved as files with the .bmerawdata extension on an external SD card. This file type is based on the JavaScript Object Notation (JSON) [38] format, which is readable by both humans and machines. Before proceeding with the preliminary data processing steps, the data in JSON format was imported into the software environment. For this purpose, JSON parsers were used, and the raw data was converted into Pandas DataFrame [39] instances to facilitate further processing.

As previously noted, each sensor matrix comprises eight sensors, and each sensor completes a measurement period comprising 10 heating steps. Consequently, a single sensor matrix produces a time series of $8 \times 10 = 80$ gas-resistance per unit of time. As the first preprocessing step, each gas resistance time series of the data frame was denoised using a low-pass filter [40]. After this filtering process, a smoother time series was obtained by removing high-frequency components from the sensor's electrical resistance signals.

In the second stage of the data preprocessing step, the classification of data in 3 datasets was performed. In the alcohol dataset, data were labelled by ethanol percentage in the mixture, whereas in the raki and whiskey datasets, classification was based on methanol content in millilitres. For example, in the alcohol dataset, a mixture containing 80% ethanol was labelled as "ethanol 80". In contrast, in the

raki and whiskey datasets, a mixture containing 3 millilitres of methanol was labelled as "methanol 3", and similar labelling was applied to other concentrations.

In the third step of the data preprocessing, the data was interpolated using single-variable spline functions [41]. Interpolation makes the data continuous, enabling the creation of synthetic samples at the required time points. The creation of synthetic data significantly expands the dataset and improves the training of classification models. Furthermore, the interpolation method was used to temporarily align the data points. The effect of the interpolation function applied to the data is seen in Fig. 10.

The electrical resistance values of the gas compost in the alcohol mixtures in all three datasets were observed to range from approximately 10^3 to 10^9 ohms. Visualising data with such large variance is difficult, and it can also suppress error functions associated with high-magnitude observations, thereby adversely affecting the stability and generalizability of both regression and classification models. To address high variance and heteroskedasticity, the data were first log-transformed. Then, standard scaling, a commonly used technique to improve the stability and convergence of machine learning training, was applied [42].

4.3. Model Selection

Regression and classification models were created using three different datasets generated during the data collection phase. The purpose of the classification models is to distinguish among different alcohol mixtures based on their gas resistance values and to assign each sample to the previously defined class. The purpose of the regression models is to create a regression curve using cases with known measurement values and to use this curve to predict cases with unknown measurement values.

This study utilised two different sensor matrices, each containing eight BME688 sensors capable of independent measurement. Sensor matrix 0 was used to measure the electrical resistance of methanol-ethanol mixtures prepared at different gas concentrations. Sensor matrix 1 was placed in an empty Erlenmeyer flask and used to measure the electrical resistance of varying, uncontrollable environmental parameters throughout the measurement period. After data collection, the electrical resistance value obtained from sensor matrix 2 was subtracted from that of sensor 1 to quantify the net effect of alcohol mixtures on the sensor output. This procedure compensated for the ambient gas composition, isolating the effect of alcohol mixtures. In other words, by identifying only the VOC values to be measured, machine learning approaches were able to produce more stable results.

Both sensor matrices were configured with the same heater profiles: HP-301, HP-354, HP-503, and HP-413. These HP profiles were sequentially assigned to the four sensor pairs in each sensor. Due to differences in measurement configurations, each heater profile yielded a different resistance value. The contribution of each temperature-modulation to the sensor pairs to model performance was evaluated separately.

Decision tree (DT), Gaussian Naive Bayes (GNB), support vector machine (SVM), logistic regression (Log. R), and multilayer perceptron (MLP) classifiers, which are frequently used in the literature for data

classification, were employed. Each developed model was trained using 5-fold cross-validation [43], and the accuracy scores were compared between different heater profiles. Classification accuracy results are presented in Table 1.

For regression, linear regression (LR), gradient-boosting regressor (GBR), stochastic gradient descent regressor (SGDR), support vector regression (SVR), and Bayesian ridge regression (BR) models were trained. The dataset was split into 80% training and 20% testing subsets. Models were trained on the training data and evaluated on the test data. Mean absolute error (MAE) and R^2 scores were computed to assess regression performance. The MAE and R^2 results are reported in Tables 2 and 3, respectively.

5. RESULTS AND DISCUSSION

Table 1 presents the classification accuracy scores of the evaluated algorithms across different heater profiles and alcohol mixture groups. As shown in the table, the support vector machine (SVM) model achieves perfect classification performance, with an accuracy of 100% across all heater profiles.

Table 1
Classification accuracy scores for Decision Tree (DT), Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM), Logistic Regression (Log. R), and Multilayer Perceptron (MLP) classifiers across the selected heater profiles: HP-301, HP-354, HP-503, and HP-413.

		DT	GNB	SVM	Log. R	MLP
Pure alc.	HP-301	0,908	1	1	0,997	0,995
	HP-354	0,96	1	1	1	1
	HP-503	0,985	1	1	1	1
	HP-413	1	0,983	1	0,98	0,985
Raki	HP-301	1	1	1	1	1
	HP-354	1	1	1	0,986	0,996
	HP-503	1	0,998	1	1	1
	HP-413	1	1	1	1	1
Whisky	HP-301	1	1	1	1	1
	HP-354	0,952	1	1	0,992	0,99
	HP-503	0,9	0,954	1	0,964	0,986
	HP-413	0,996	1	1	1	1

Table 2 presents the mean absolute error (MAE) scores of the regression models for predicting the methanol concentration in alcohol mixtures. The gradient boosting regressor (GBR) achieves a perfect

MAE score of 0 when trained on data generated using the HP-301 or HP-503 heater profiles across all three alcohol mixture groups. Considering the R2 values in Table 3, it is observed that the GBR model, which has the best performance in predicting methanol concentration in different alcohol types (Alcohol, Raki, and Whiskey Dataset), is again the best, in parallel with the MAE results in Table 2.

Table 2
MAE scores of linear regression (LR), gradient boosting regressor (GBR), stochastic gradient descent regressor (SGDR), epsilon-support vector regression (SVR), and Bayesian ridge regression (BR) models across the selected heater profiles: HP-301, HP-354, HP-503, and HP-413. Lower MAE values indicate better performance.

		LR	GBR	SGDR	SVR	BR
Pure alc.	HP-301	0,77	0	1,133	2,057	0,767
	HP-354	0,802	0,011	1,296	0,985	0,798
	HP-503	0,532	0	0,84	0,817	0,533
	HP-413	0,543	0,036	0,822	1,215	0,543
Raki	HP-301	0,126	0	0,407	0,099	0,126
	HP-354	0,219	0	0,463	0,111	0,22
	HP-503	0,13	0	0,337	0,098	0,13
	HP-413	0,176	0	0,383	0,127	0,175
Whisky	HP-301	0,192	0	0,377	0,095	0,193
	HP-354	0,164	0	0,417	0,086	0,163
	HP-503	0,125	0	0,274	0,097	0,124
	HP-413	0,099	0	0,283	0,109	0,098

When the results are interpreted in terms of temperature modulation profiles (HP), as seen in Tables 1, 2, and 3 in the classification and regression models, it is thought that the BME 688 gas sensor shows near-perfect performance for methanol detection and concentration in alcoholic beverages when configured with HP-301 or HP-503 heater profiles.

In conclusion, for the detection and classification of methanol in widely consumed potable distilled spirits, SVM-based models perform best, regardless of temperature modulation. Furthermore, for detecting methanol in pure alcohol, the best combination of temperature modulation and algorithm is achieved by models that integrate the SVM algorithm across all temperature-modulation profiles. To determine methanol concentration in pure alcohol, i.e., to generate the regression curve, the most successful temperature-modulation and algorithm combination was the model resulting from integrating the HP-301 and HP-503 temperature profiles with the GBR algorithm. In contrast, for determining

methanol concentration in commonly sold potable distilled alcohol blends, the GBR algorithm provided the best results, regardless of temperature modulation.

Table 3

Coefficient of determination (R^2) scores of linear regression (LR), gradient boosting regressor (GBR), stochastic gradient descent regressor (SGDR), epsilon-support vector regression (SVR), and Bayesian ridge regression (BR) models across the selected heater profiles: HP-301, HP-354, HP-503, and HP-413. Higher R^2 values indicate better performance.

		LR	GBR	SGDR	SVR	BR
Pure alc.	HP-301	0,997	1	0,994	0,955	0,997
	HP-354	0,997	1	0,991	0,992	0,997
	HP-503	0,998	1	0,996	0,994	0,998
	HP-413	0,999	1	0,997	0,987	0,999
Raki	HP-301	0,999	1	0,992	0,999	0,999
	HP-354	0,998	1	0,991	0,999	0,998
	HP-503	0,999	1	0,994	0,999	0,999
	HP-413	0,999	1	0,993	0,999	0,999
Whisky	HP-301	0,998	1	0,992	1	0,998
	HP-354	0,999	1	0,992	1	0,999
	HP-503	0,999	1	0,997	1	0,999
	HP-413	1	1	0,996	0,999	1

6. CONCLUSIONS

This study demonstrates that the BME688 gas sensor can detect the presence and quantify the concentration of methanol in distilled potable alcohol. The results show that, when gas-composition electrical-resistance data from the BME 688 sensor are combined with appropriate preprocessing techniques and machine-learning algorithms, the resulting predictions are highly accurate and reliable. However, this approach is better suited to serve as a screening layer for early warning and preliminary risk assessment, rather than as an alternative to confirmatory reference laboratory methods as a first step.

Given that even small amounts of methanol are highly toxic to humans, potentially leading to irreversible health damage, coma, or death, its rapid and reliable detection in alcoholic beverages is of critical

importance. As a low-cost, lightweight, and low-power sensor, the BME 688 offers a practical alternative to conventional laboratory-based analytical methods. Its deployment in alcohol production facilities and along supply chains could enable early-stage screening and continuous monitoring, thereby reducing the risk of methanol-related health hazards. Moreover, the proposed approach has the potential to lower operational costs by minimising dependence on expensive laboratory equipment and controlled testing environments.

Beyond its immediate applicability, this study highlights the broader potential of integrating low-cost gas sensors with machine learning techniques for chemical safety monitoring. The strong performance observed in both classification and regression tasks suggests that such sensor–algorithm combinations may provide scalable, adaptable solutions for real-world quality-control applications. In particular, the ability not only to detect methanol but also to estimate its concentration enhances the system's practical utility, enabling more informed decision-making in safety-critical contexts.

Nevertheless, several limitations should be acknowledged. The experiments were conducted under highly controlled laboratory conditions and involved a limited number of alcoholic beverage samples. As such, the generalizability of the results to real-world settings where temperature, humidity, background gases, and beverage compositions may vary significantly remains to be fully established. Future work should therefore focus on validating the proposed approach across a broader range of alcoholic beverages, methanol concentrations, and environmental conditions, and on assessing long-term sensor stability and robustness.

In future studies, integrating additional sensor modalities, adaptive calibration strategies, and advanced learning frameworks such as domain adaptation or online learning may further enhance system performance and resilience. Such developments could enable practical, deployable methanol detection systems that meaningfully contribute to public health protection and food safety assurance.

Declarations

Conflicts of Interest

The author declares that there are no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

İ.H.P., M.M. and N.S.M. designed and performed research, analyzed data and wrote the paper. F.D. and S.T. assessed the results and took part in writing the paper.

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Data Availability

The data and source code described and used in this article are available and can be accessed at <https://github.com/ihpar/methanol>.

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Figures

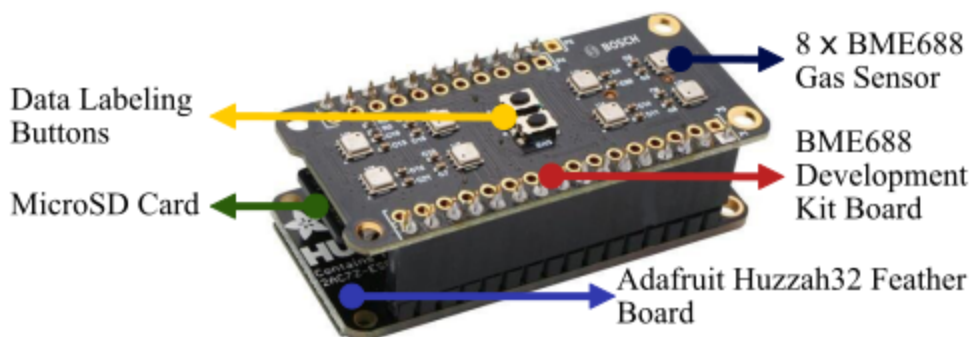


Figure 1

Sensor matrix containing 8 BME688, used for environmental measurements [24].

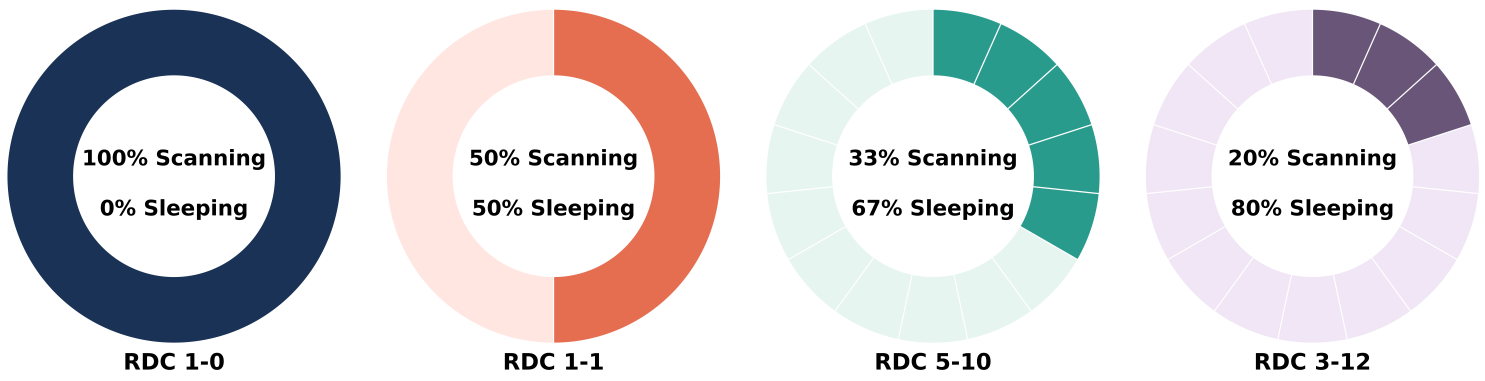


Figure 2

Different RDC profiles can be used across a range of application scenarios (Adopted from [31].)

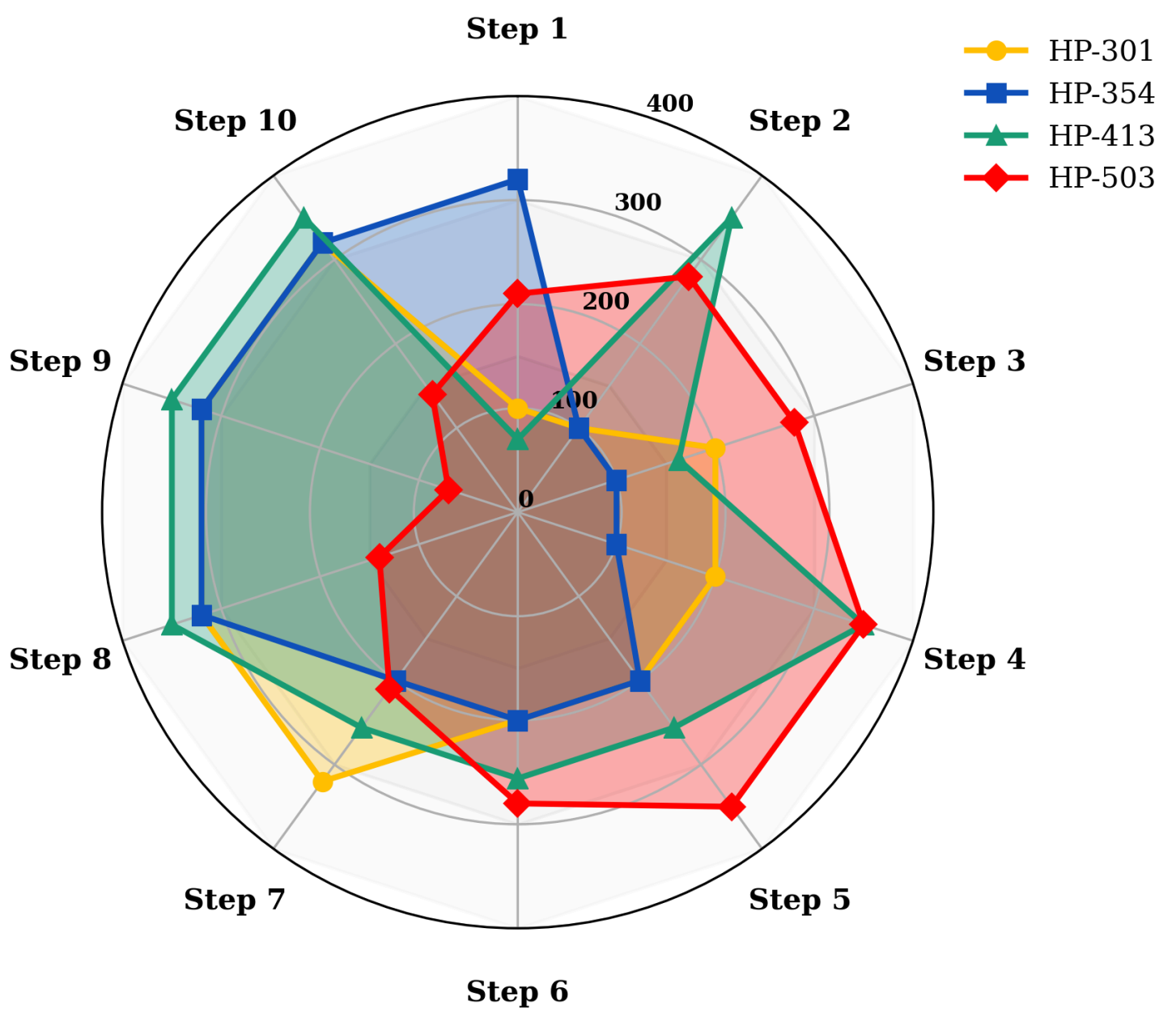


Figure 3

4 different temperature modulation profiles are used for ambient measurements. (Adopted from [31].)

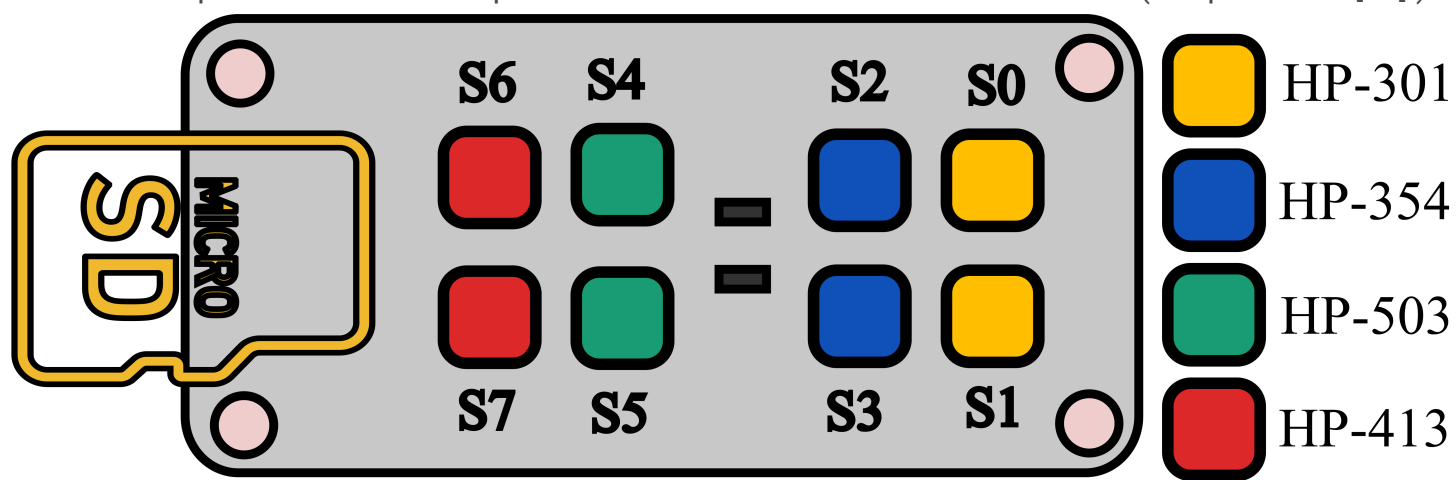


Figure 4

Heater Profile configuration of the sensor pairs included in the sensor kit.



Figure 5

A view of the experimental setting where mixtures of pure methanol and ethanol were used for measurement.

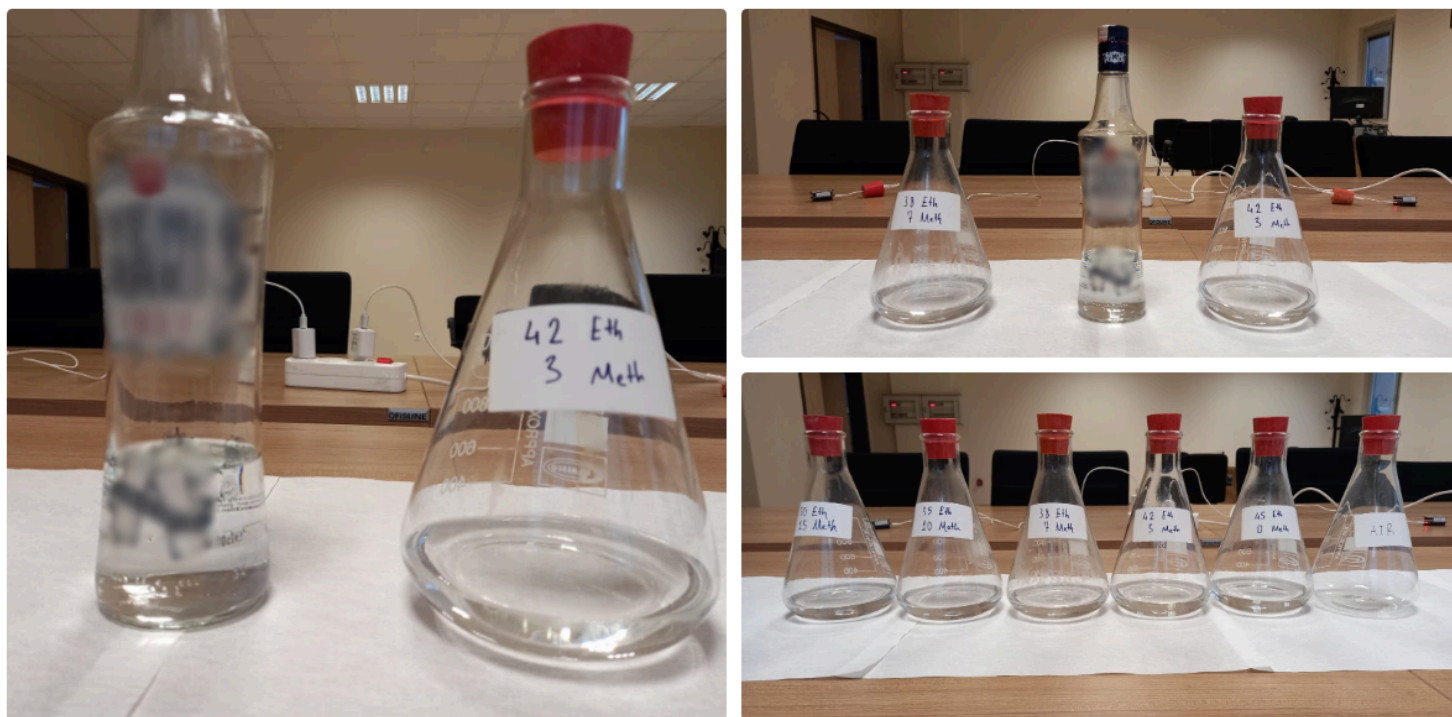


Figure 6

An experimental setup for detecting the presence and concentration of methanol in Raki using a sensor.



Figure 7

An experimental setup for detecting the presence and concentration of methanol in Whisky using a sensor.

Alcohol (Sample) Sensor 3

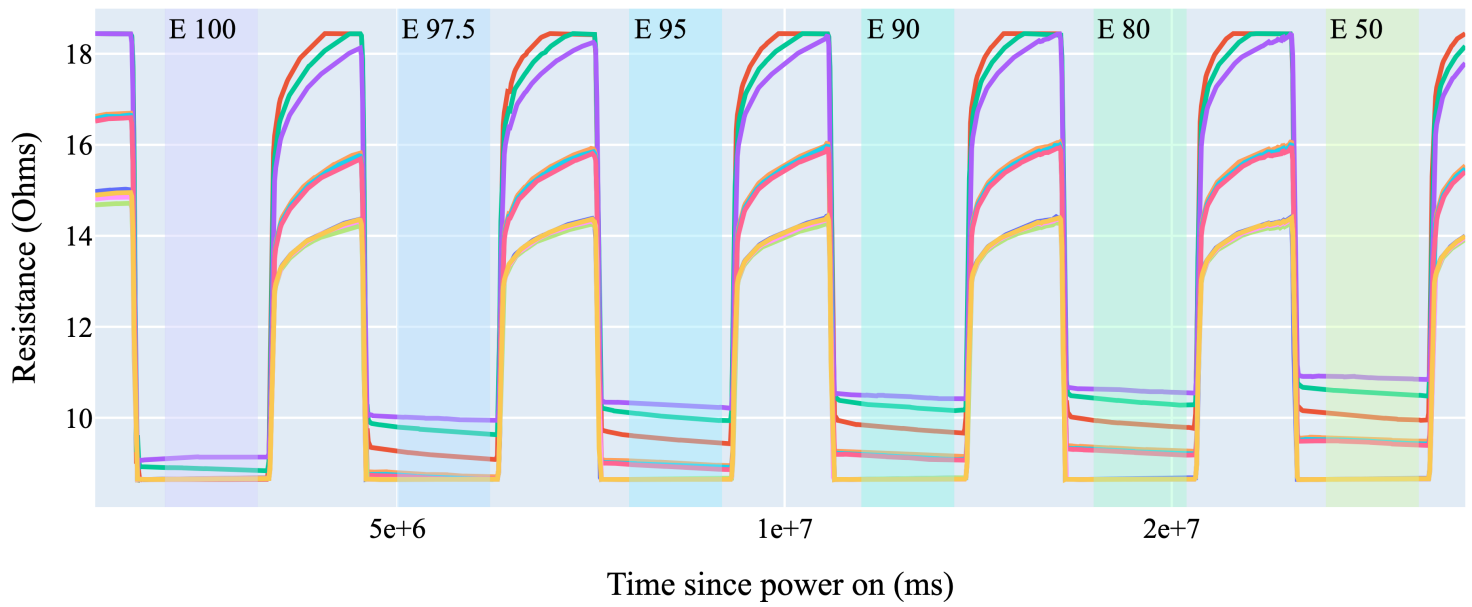
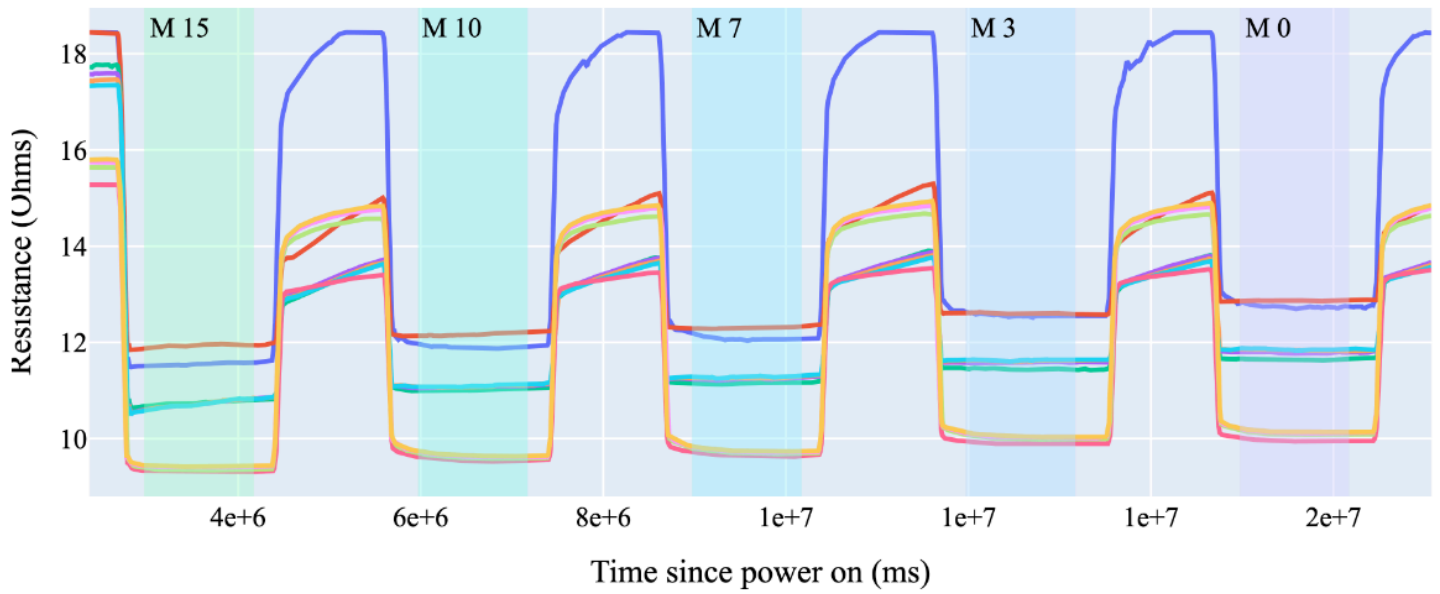


Figure 8

The graphs show the raw data from sensor 3 in the alcohol dataset, along with the dataset's classes.

Rak1 (Sample) Sensor 1



Whisky (Sample) Sensor 7

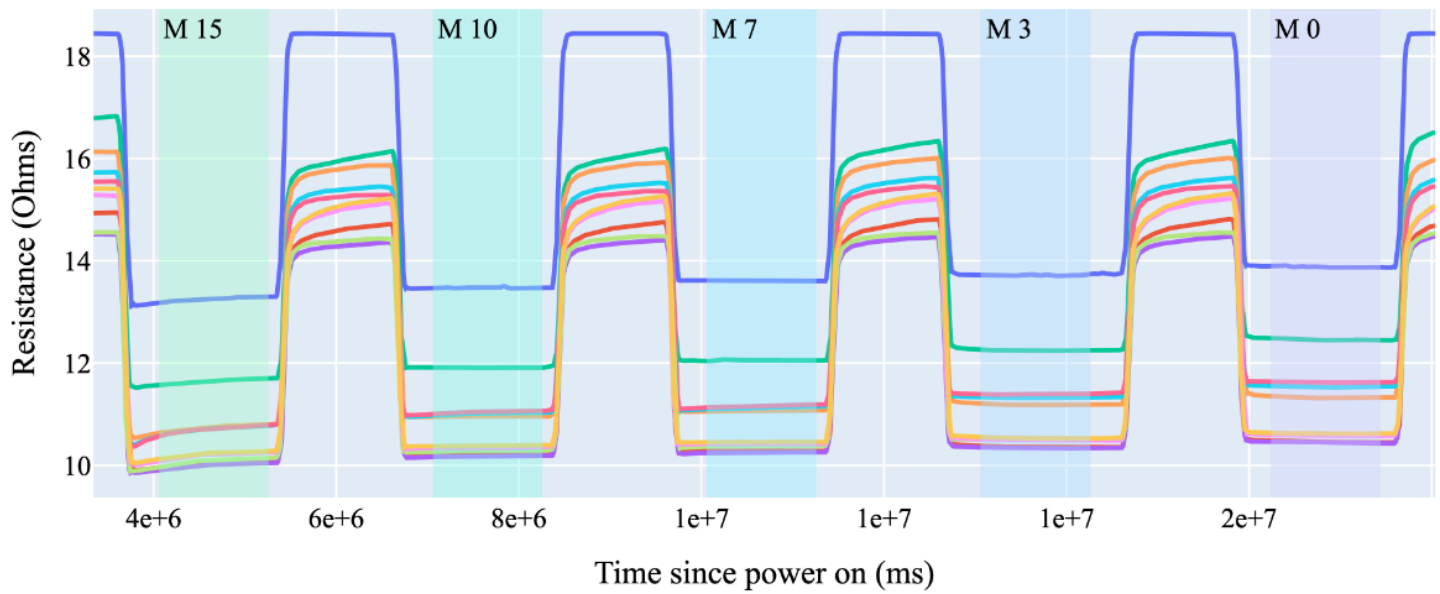


Figure 9

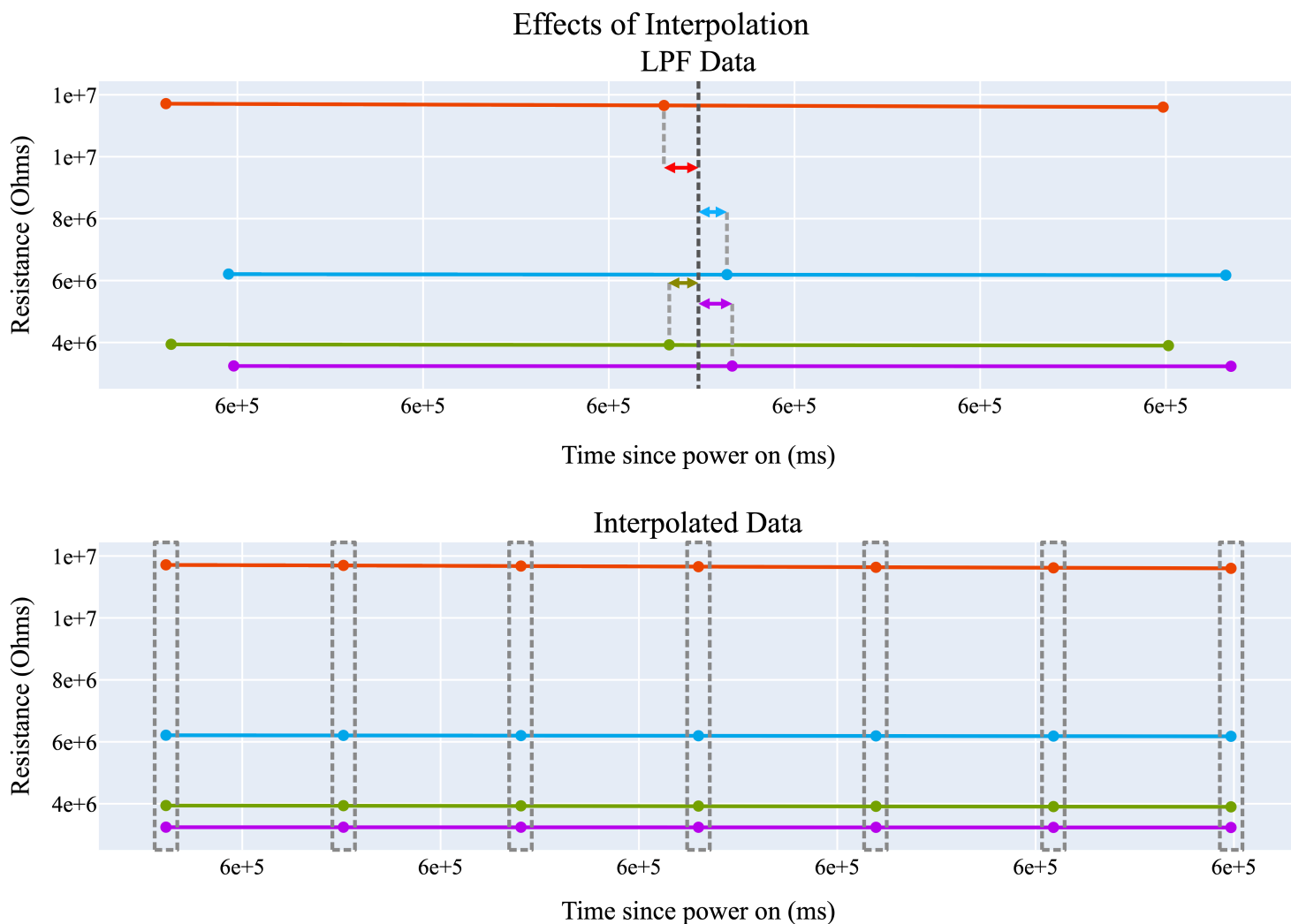


Figure 10

Effect of the interpolation function applied to the data. Non-interpolated samples are shown on the top graph. Interpolated and time-aligned samples are shown on the bottom graph.

Supplementary Files

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