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Climate Change Sensing through Terahertz Communication Infrastructure: A Disruptive Application of 6G Networks

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***Abstract*—Climate change resulting from releasing greenhouse gases into the atmosphere continues to affect the Earth's ecosystem. This pressing issue is driving the development of novel technologies to sense and measure harmful gas emissions. In parallel, the evolution of wireless communication networks requires the wider deployment of mobile telecommunication infrastructure. The terahertz (THz) spectrum is currently under-utilized but is expected to feature in 6G. The use of this spectrum is explored simultaneously for ultra-broadband communication and atmospheric sensing. For atmospheric sensing, the absorption of THz signals by gas molecules is used to estimate atmospheric gas composition. Molecular absorption loss profiles for each gas isotopologue are taken from the HITRAN database and compared with data from transceivers in *sensing mode*. Preliminary results are presented, showing the effects of signal path loss and power spectral density. A 6G network architecture is proposed to indicate how 6G infrastructure can perform climate change sensing, in addition to its primary purpose of wireless communication.**

***Index Terms*—Terahertz communication, 6G, climate change, atmospheric sensing.**

INTRODUCTION

CLIMATE change is one of the most pressing challenges for the sustainability of the planet in the twenty-first century. Challenges include global temperature rise with warmer oceans and shrinking ice sheets, contributing to rising sea levels and ocean acidification. The impact of all these changes on the planet is being witnessed today through more frequent extreme weather events. Researchers believe that global climate trends will worsen significantly in the coming decades, given increasing greenhouse gas concentrations from human activities such as expanding industries, transport and agricultural activities. All these activities emit greenhouse-effect gases such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), among others. Such gases allow sunlight to pass through the Earth's atmosphere but trap the resulting heat near the surface, thereby contributing to global warming. Sensing greenhouse gases and other harmful gases (e.g., ground-level ozone) will allow humanity to plan for the future by developing strategies to reduce harmful gas emissions. Rather than using conventional sensor networks to detect these gases, novel sensing techniques can be created without requiring a) massive deployment effort and costs, b) ongoing maintenance, and c) massive material resources (in the form of specialized sensing infrastructure).

While the telecommunications industry is rolling out 5G globally, the research community is busy researching new disruptive technologies. 6G is expected to progress into the upper millimeter-wave (100-300 GHz) and the terahertz (0.3-10 THz) spectrum. The *larger bandwidth available at THz frequencies* (up to hundreds of contiguous GHz) has the potential to provide high data rates, approaching a terabit-per-second (Tbps) or more. The *shorter wavelength of the THz spectrum* (less than a millimeter) enables both the creation of miniature antennas for nanoscale machine communication in nanonetworks, as well as, through the integration of many such antennas into high-density antenna arrays, the design of highly directional THz links with a low probability of detection and interception [1]. Beyond communications, the combination of very short wavelengths with the *higher photon energies of THz radiation* (though still lower than that of optical signals) improves the resolution and accuracy of traditional radar systems and enables new sensing techniques, including spectroscopy-based classification of media [2]. Indeed, several frequencies in the THz band are known to be strongly impacted by molecular absorption, and thus, traditionally, communication systems have avoided those frequencies. However, by changing our perspective, molecular absorption at THz frequencies might also enable atmospheric sensing technologies [1]. For example, multiple satellites orbit the Earth, having THz sensors for atmospheric studies. In addition, industrial technologies utilize the absorption profiles of the THz spectrum to sense specific atmospheric gases, and these technologies have applications in the area of Environmental Monitoring, Breath analysis, and Natural gas sensing [3].

In our vision, 6G infrastructure might offer the opportunity to integrate communications and sensing in a new way. At lower frequencies (using dedicated individual point-wise sensors), joint communications and sensing usually means communications and radar for sensing and localization. However, innovative 6G infrastructure could simultaneously satisfy the connectivity needs of a hyper-connected society while collecting an unprecedented amount of data to monitor gases associated with climate change. Frequency switching using an antenna array comprising nano-antennas working at different frequency bands [4] for sensing is needed to implement this concept. This is because transceivers used for

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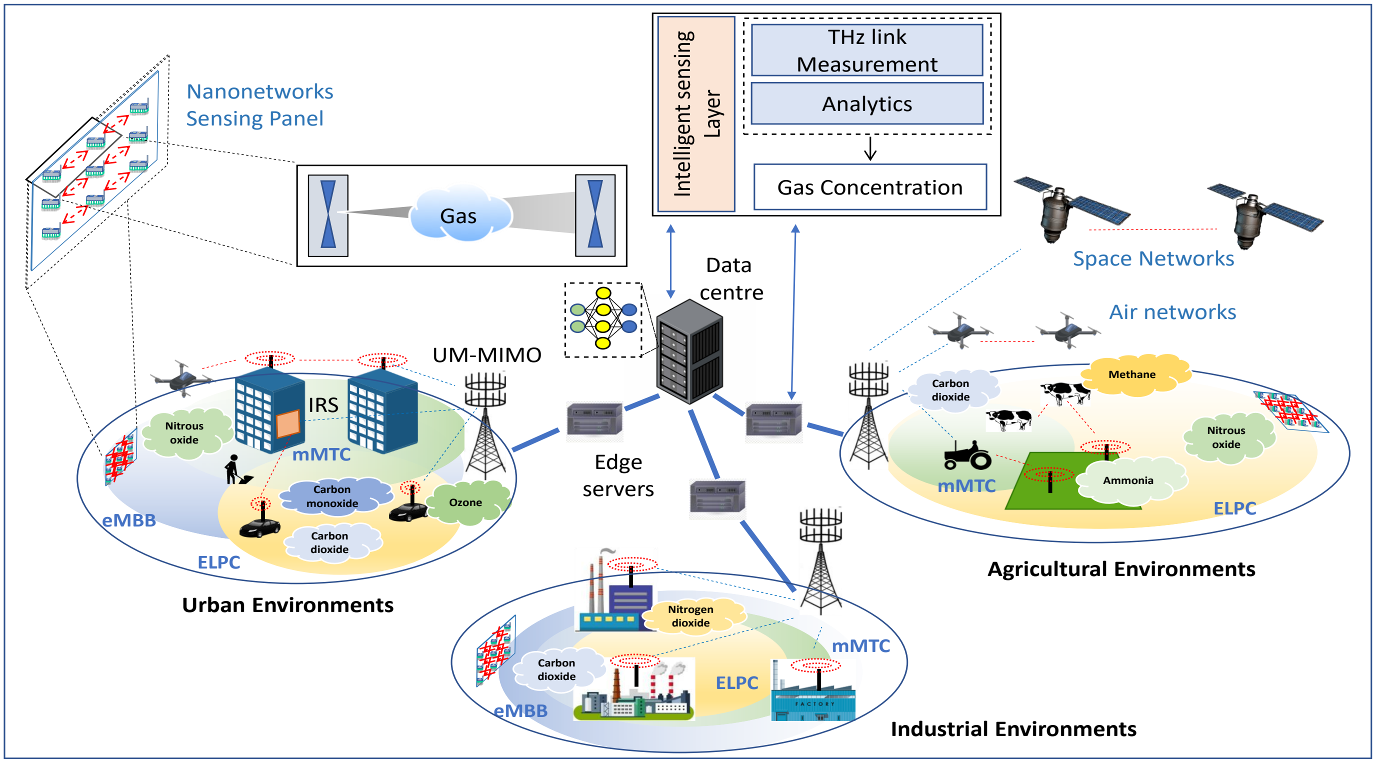

Fig. 1: 6G Network architecture for communication and sensing.

communication avoid THz frequency ranges where high levels of molecular absorption disrupt communications, but such frequencies are needed for sensing. Therefore, our objective is to utilize selected frequency ranges that are unsuitable for communication but are chosen to measure certain atmospheric gases. Moreover, current atmospheric sensing systems rely on frequency chirps or chirp spread spectrum. However, for sub-terahertz and terahertz systems, single-carrier modulations are preferred due to the multi-carrier systems' high peak-to-average power ratio penalty. Advanced solutions [5] use the chirp's simultaneous amplitude and phase modulation, with proper amplitude compensation during radar response measurement. In Fig. 1, we illustrate our architecture for joint communications and sensing of atmospheric gases using 6G infrastructure.

Artificial Intelligence (AI)-integrated communication technologies of enhanced Mobile Broadband (eMBB), massive Machine Type Communication (mMTC), and Extremely Low Power Communication (ELPC) will utilize novel infrastructures, such as ultra-massive MIMO transceivers, intelligent reflecting surfaces (IRS) based on novel plasmonic reflect-arrays or metasurfaces, and even non-invasive pervasive deployments of nanonetworks. The increased use of antenna arrays in ultra-massive multiple-input multiple-output (UM-MIMO), coupled with passive IRS, will result in a spatial blanket of THz signals covering regions with challenging communication needs, requiring extensive infrastructures. Also, the *nanonetwork* devices have miniature form-factors built of metamaterials to support communication at THz frequencies.

Highly-anticipated applications include automated driving, holography, tactile and haptic internet and new forms of connectivity (e.g., unmanned aerial vehicles (UAVs) operating as wireless repeaters in remote areas. Such infrastructure will also enable distributed atmospheric sensing for climate change monitoring, pollution, and air quality control. The collected data will be analyzed in real-time in edge servers or data centers by means of an Intelligent Sensing Layer. The goal is to measure the targeted gas concentration in a particular location under various environmental conditions. Machine learning (ML) will play a key role in analyzing the massive amount of collected data.

In this paper, we explore this vision for the first time, and discuss how THz signal analysis can be used to determine changes in gas concentration that impacts the climate. This will open new opportunities to collect gas concentration data using readily available telecommunication infrastructure, without requiring the extra cost of dedicated sensors, maintenance (e.g., replacing batteries), and materials incurred by networks of dedicated atmospheric gas sensors. This paper is organized as follows. The next section overviews the current sub-terahertz and terahertz technologies used for gas sensing. Then, we present our proposed 6G infrastructures for sensing gases in various environments. Then we present preliminary results, using ML to extract sensing information from measured path loss and received signal power spectral density. Finally, we identify the challenges that need to be addressed to enable this transformative paradigm and conclude the paper.

Sub-Terahertz and Terahertz Gas Sensing Technologies

Many gases emitted from agricultural, manufacturing, and industrial processes, as well as urban environments more generally, are harmful pollutants and contribute to the greenhouse effect. Interestingly, in most of these cases, the gases can be detected using THz spectroscopy. THz spectroscopy is a powerful analytical technique based on electromagnetic radiation's absorption, reflection, or transmission in the THz frequency range. One of the main advantages of THz spectroscopy is that it can reveal the collective behavior of large molecules in a sample, providing information about the vibrational and rotational modes of molecular systems. Moreover, its accuracy and efficiency are significant trade-offs under a controlled indoor environment. However, large-scale outdoor deployment of THz spectroscopy sensors is challenging. Photonics-based THz sources are expected to suit sensing applications, where broadband signals and frequency sweeps are essential. However, electronics-based THz sources are more widely utilized due to the drawbacks of photonics-based THz sources, such as coherence affecting the ability to extract accurate information from the received signal, power limitations affecting long-range THz communication, the complexity of integration into practical communication systems and the potential of increasing the overall system cost. At sub-THz frequencies and lower, signal strengths are sufficient to enable both communications and sensing over tens or hundreds of meters (this communication range has been experimentally proven [6]). However, higher frequencies with short-range communications will be used to sense gases such as ammonia (NH_3) and methane (CH_4) (see Table I), relying on a nano-network of THz devices that will be integrated into the wireless infrastructure. We summarize THz sensing technologies that can be used to sense toxic, pollutant, and greenhouse gases.

Sensing for Agricultural Environments

- Ammonia (NH_3) is a gas found extensively in farming environments, released by the breakdown of artificial fertilizers and animal manure. Excessive exposure to NH_3 can negatively impact health and environmental biodiversity. In [7], THz frequencies have been used for NH_3 gas and water vapor (H_2O) sensing using THz Time-Domain Spectroscopy (TDS) transmission measurement geometry.
- Plants and vegetables emit Volatile Organic Compounds (VOCs) gases such as acetonitrile (C_2H_3N), ethanol (C_2H_5OH), and methanol (CH_3OH) from leaves. These gases can adversely affect the human body. For example, acetonitrile can transform into cyanide within the body. THz wave spectrometry has been utilized for VOC gas sensing [3].

Sensing for Industrial and Urban Environments

Sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and carbon monoxide (CO) are some of the most prevalent pollutant gases found in the atmosphere. These gases mostly enter the atmosphere when fossil fuels are burnt.

- SO_2 contributes to pollution through acid rain. Inhalation of SO_2 can irritate the respiratory tract, leading to an increased risk of infections, coughing and excessive mucus secretion. The gas can be detected utilizing electronic submillimeter/terahertz (SMM/THz) gas sensors [3].
- Similarly, NO_2 also leads to acid rain through the production of nitric acid. Prolonged exposure to high levels of NO_2 can result in chronic lung disease. In addition, high levels of NO_2 can damage foliage, decreasing growth or reducing crop yields. Continuous-wave electronic THz spectrometers can sense NO_2 in the frequency range of 220-330 GHz [8].
- CO is also harmful since it readily displaces oxygen in the bloodstream and can lead to asphyxiation, and the gas can be detected using THz Gas-phase spectroscopy (THz-GPS) in the frequency range of 0.3-1.1 THz [9].
- Plants can naturally produce hydrogen cyanide (HCN), and industries such as mining release it as a waste product with wastewater. HCN found in wastewater can also be found in gas form, which can be detected using photonic crystal cavity detection techniques at frequencies of 1.1–1.3 THz [10].
- CO_2 emitted by industrial processes and burning fossil fuels is the dominant but not the only greenhouse gas responsible for global climate change. Other gases that create greenhouse effects include CH_4, N_2O, ozone (O_3), and Fluorinated gases such as tetrafluoromethane (CF_4). In [11], THz spectroscopy is used to detect these gases in an atmospheric simulation chamber using frequency ranges 2-2.7 THz and 0.575–0.625 THz for CH_4, CF_4, N_2O and O_3, respectively.

6G for Climate Change Action

Building on the indicated possibility of utilizing THz signals to sense critical gases impacting climate change, in this section, we present innovative 6G THz network infrastructures that can bring the vision of joint communications and gas sensing to reality.

Terahertz and Sub-Terahertz Absorption Properties

In addition to the high spreading losses resulting from the very small wavelength of THz signals, which requires the utilization of high gain directional antennas with narrow beams, THz signals are also affected by molecular absorption and, to a lower extent, scattering by dust particles, fog, snowflakes, or rain droplets. The main absorber of THz radiation is water vapor, H_2O, which has resonances across many THz frequencies leading to extremely high absorption [2]. However, as highlighted in the previous section, THz radiation is absorbed by many gases, including SO_2, O_2, NH_3, and CH_4, and each gas has a unique absorption profile, which opens new opportunities for using THz signals for sensing.

Our sensing concept is based on the molecular absorption profiles, by frequency, that are unique to each gas. Figure 2 illustrates simulated molecular absorption losses of THz signals using data from the high-resolution transmission (HITRAN) molecular spectroscopic database [12] under standard temperature (296 K), and pressure (1 atm) at 5 cm distance for O_3, SO_2, and NO_2 when they are mixed with other gases based on their atmospheric concentrations [13]. In our measurement model, each standardized absorption profile uniquely identifies a gas, and absorption levels increase with the concentration of

	Proposed technique using path loss				Techniques developed using spectroscopy		
Gas	Atmospheric concentration (ppm)	Considered frequency range	Gaussian noise level	Possibility of detection	Frequency range	Detection techniques	Reference
H_2O	10000	6–8 THz	1 %	Yes	0.1–2.25 THz	THz-TDS	[7]
O_2	209460	0.5–2.5 THz	0.01 %	Yes			
SO_2	1	0.5–2.5 THz	0.01 %	Yes	0.21-0.27 THz	Electronic SMM/THz gas sensor	[3]
NH_3	0.01	3–5.5 THz	0.01 %	Yes	0.1–2.25 THz	THz-TDS	[7]
O_3	0.07	1-3 THz	0.001 %	Yes	0.575–0.625 THz	THz-TDS	[11]
NO_2	0.02	1–3 THz	0.001 %	Yes	0.22-0.33 THz	Continuous-wave electronic THz spectrometer	[8]
HCN	0.01	1–3 THz	0.001 %	Yes	1.1–1.3 THz	Photonic crystal cavity	[10]
CO	0.01	0.5–3 THz	0.0001 %	Yes	0.3-1.1 THz	THz-GPS	[9]
CH_4	1.8	3-4.5 THz	0.00001 %	Yes	2–2.7 THz	THz-TDS	[11]
N_2	780840	3–5 THz	Reduced until 0.000001 %	No			
CO_2	410	8–10 THz	Reduced until 0.000001 %	No			
N_2O	0.5	0.1–1.5 THz	Reduced until 0.000001 %	No	0.575–0.625 THz	THz-TDS	[11]
CH_3OH	0.01	0.1–1 THz	Reduced until 0.000001 %	No	0.22–0.33 THz	THz wave electronics	[3]

TABLE I: Impact on Gaussian noise level on path loss data analysis for gas concentration measurements.

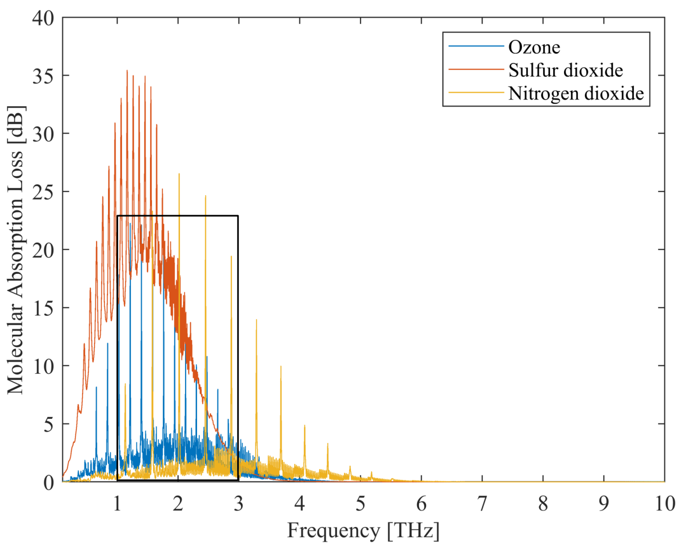

Fig. 2: Simulated molecular absorption losses of THz signals for ozone, sulfur dioxide, and nitrogen dioxide using HITRAN data.

that gas. For instance, Fig. 2 shows that SO_2 has the highest absorption, and so requires lower measurement sensitivity than NO_2 or O_3 over that range of frequencies.

The measurement sensitivity of the proposed system is inversely related to its Gaussian noise (See Table I for how this inherent Gaussian noise affects gas measurement capability). The Gaussian noise is a function of transmitted power, frequency, and the capabilities of both the transmitter and receiver. A smaller Gaussian noise level indicates greater measurement capability. For example, referring to Table I, if the Gaussian noise level is 0.01%, gases of interest such as NH_3 and SO_2 can be detected reliably, but not other gases like O_3, which would require greater measurement system capability (equivalently, smaller relative Gaussian noise).

Agricultural Environments

Future farming environments are expected to have multiple sensing devices under the guise of Internet of Everything, communicating to 6G through mMTC as well as ELPC for Internet of Bio-Nano Things and Internet of Nano Things. The connectivity of these devices can be established through ultra-cells [14], which have been proposed for transmitting short-range THz signals. While connectivity from ultra-cell to macrocell will be a problem in rural areas such as farms, the ultra-cells can provide connectivity to local devices and perform edge-based computing, and can send data to the macrocell (e.g., via UAVs). To redirect beams within farming sheds, where equipment and facilities cause obstruction, passive IRS can be used. Suitable ultra-cells might be placed within milking sheds for confined areas to sense CH_4 emission as cows are being fed, as well as sensing NH_3 and SO_2 from the slurry. Ruminants such as cattle contribute to greenhouse gases, particularly CH_4, when digesting their food. A single cow typically emits approximately 200 pounds of CH_4 gas per year. Farm livestock produces other greenhouse gases such as CO_2 and N_2O. Passive IRSs with ultra-cell-based networking can be utilized to transmit signals in 0.5-1.0 THz frequency to detect a target gas over a distance of more than 1 m, and nanonetwork devices on the active IRSs itself can be used to sense local gases such as CH_4 and SO_2 over distances less than 1 m. Passive IRS-enabled communication to a mobile vehicle, such as a tractor or drone, might also facilitate outdoor gas sensing.

Industry and Urban Environments

Industrial and urban environments produce greenhouse gases such as CO_2 and N_2O, mainly as a result of human activities. CO_2 is a major contributor to the global warming crisis. Major industrial sectors producing CO_2 include power

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generation (54 percent), cement production (15 percent), gas processing (12 percent), iron refining (6 percent), petroleum refining (5 percent), and chemical plants such as C_2H_5OH and NH_3 (3 percent) producers. Additionally, large amounts of CO_2 are emitted from residential areas in urban environments when energy is consumed. Therefore, outdoor infrastructures are the most appropriate for sensing these gases. Ultra-massive MIMOs on macrocells, communicating to picocells and femtocells at 0.1-5 THz, offer opportunities for sensing in industrial and urban environments. Also, using UM-MIMO base stations at 0.3 THz and 1 THz frequency, multi-Tbps links are achievable for communication [15]. Moreover, the deployment of femtocell and picocell base stations under the footprint of macrocell base stations reduces the distance between the sensing devices and helps to maintain a high signal-to-interference and noise ratio (SINR) while sensing. Furthermore, picocell base stations are mounted on high-rise buildings or infrastructures in dense urban areas because of their limited coverage [14]. Again, outdoor passive IRS can also play a significant role in redirecting beams between the cells, and Vehicle to Infrastructure (V2I) communication using THz links can take advantage of frequencies that are unused for communication to provide roadside sensing. This dual use of the infrastructure facilitates gas sensing at ground level in urban environments.

In both agricultural and industrial environments, we assume a private network for communication and sensing. However, in urban environments, the ultimate goal would be to integrate our systems within the Open Radio Access Network (O-RAN) architecture, which is part of our future work.

Detection Techniques

Similar to 5G, 6G will use machine learning (ML) to analyze and process large data sets for its own network management, as well as supporting its use in applications. Here, we propose how ML can be used to infer gas concentrations from measurements of path loss and power spectral density (PSD).

Path Loss Data Analysis

Path loss analysis measures the attenuation factor and uses that information to measure gas concentration. We focus on the molecular absorption loss per frequency rather than the total path loss, which includes spreading loss. The spreading loss is based purely on the distance and the transmitter and receiver antenna properties at the target frequency and is not affected by the channel medium. The detection accuracy is determined by the ratio of Gaussian noise (N) to absorption loss in the received signal. Table I summarises this for a variety of gases at a ratio specified by the atmospheric concentration, where we can see that each gas type will have a corresponding maximum tolerable Gaussian noise limiting accurate detection. We also compare the frequency range in our study with the frequency range used in THz-spectroscopy based sensing techniques. Our analysis uses data from the HITRAN molecular spectroscopic database [12], and was established by controlling the noise level (P) and reducing it step-by-step when solving the multiple linear regression problem based on equation (1).

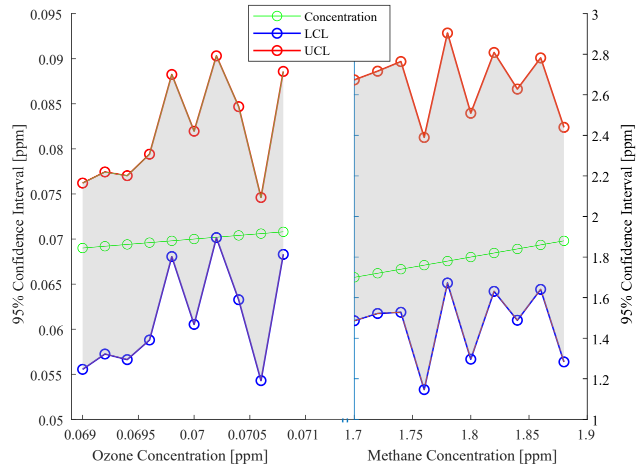

Fig. 3: Measurement sensitivity curve for ozone and methane, showing expected gas concentrations and the confidence intervals (LCL: Lower Confidence Level, UCL: Upper Confidence Level) of the predicted gas concentrations.

$$\text{Total}_{\text{Abs}} = \sum_{i=1}^{n} C_{g_i} Abs_{g_i} + PN, \tag{1}$$

where $\text{Total}_{\text{Abs}}$ is the total molecular absorption loss and C_i and Abs_{g_i} are the measurable concentrations and absorption loss profiles, respectively, of each gas g_i. The linear least squares technique we used includes the following constraints: a) the concentrations of each gas should be less than one million ppm, and b) the sum of the concentrations should equal one million ppm. The results in the table are based on 1000 Monte Carlo simulations to estimate the effects of randomness. Our simulations gradually decreased the Gaussian noise level until 0.000001 percent, and many of the gases in the mixture were detectable and measurable at this 0.00001 percent noise threshold. The expected atmospheric gas concentrations (in ppm) from Table I are used to generate molecular absorption loss profiles for typical atmospheric gas mixtures. Gaussian noise is added to the generated absorption losses in a controlled way, as described above, and then we try to estimate each gas in the presence of this noise. Some gases, like H_2O, can be measured even with 1 percent added noise, but there is much less sensitivity for gases like N_2O.

As an example, Fig. 3 shows how we used the multiple linear regression model to predict the concentration of O_3 and CH_4 at 5 cm distance for the frequency range of 1.0-3.0 THz and 3.0-4.5 THz, respectively. Similarly, we accurately predict the gas concentrations of other detectable gases in their considered frequency ranges mentioned in Table I. The frequency range with the highest molecular absorption loss for the specific gas type is chosen (see the highlighted rectangular area in Fig. 2 for O_3). The measurement sensitivity curves for O_3 and CH_4 were generated at the 0.001 percent and 0.00001 percent Gaussian noise levels, respectively. The results in Fig. 3 show that we can establish 95 percent confidence intervals (CI's) of the predicted gas concentrations that only deviate from the

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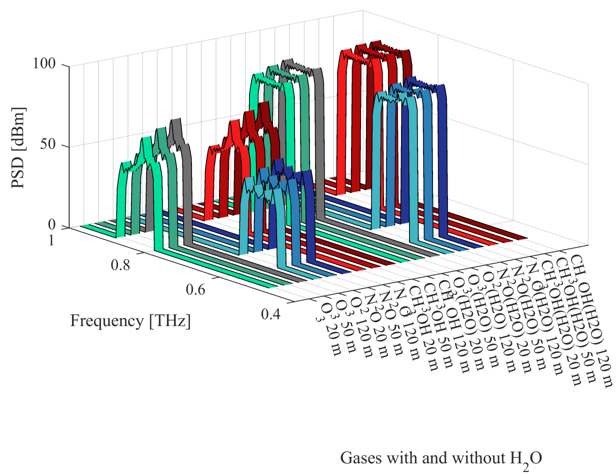

Fig. 4: Total power spectral density for ozone, nitrous oxide, and methanol considering a mixture with and without water vapor and varying distance between transmitter and receiver.

actual concentration by a small percentage (this is bounded by the upper confidence levels (UCL) and lower confidence levels (LCL)). The other gases, such as nitrogen (N_2), CO_2, N_2O, and CH_3OH are not measurable using path loss data for any of the considered THz frequencies because the measurement sensitivity is too low.

Power Spectral Density Data Analysis

We use PSD measurement analysis to sense a targeted gas in a mixture. Figure 4 presents the power spectral densities of O_3 in 0.59–0.69 THz and N_2O and CH_3OH in 0.8–0.9 THz frequency bands by considering a scenario of sending 0.05 nanoseconds long pulsed chirp signals through a gas mixture with and without H_2O, while also varying the distance between the transmitter and receiver. A pulsed chirp signal can sweep through all the required frequencies. We analyzed the molecular absorption loss of the targeted gases when mixed with H_2O, O_2, and N_2 to select the narrow frequency ranges that will result in low absorption loss by H_2O and high absorption loss for the target gas. Our results show a significant impact from H_2O on the PSD measurement corresponding to the molecular absorption noise, as well as the attenuation effect of distance. This impact on the overall PSD measurement is summed with the PSD corresponding to the chirp signal in the frequency domain. The shapes in Fig. 4 indicate that it is possible to estimate gas concentrations by applying chirp spread spectrum signals and using supervised-learning techniques.

Our PSD analysis also considers sensing a target gas when its gas concentration varies in the atmosphere by 0.5, 0.75, 1.25, and 1.5 times from the expected level. This analysis is needed because mammals need to breathe a mixture of gases to survive, and it can be harmful or even toxic if certain gas concentrations are higher/lower than normal. The typical variation in atmospheric gas concentration is relatively small, so differences in the PSD measurements are expected to be minimal. However, we do not intend to detect the differences directly using the proposed system but to process the current PSD for the target gas at the altered level. Thereafter, the proposed intelligent sensing layer will detect small variations in gas concentrations relative to previously maintained training data. Moreover, due to turbulence in the network (e.g., changes in humidity, power supply instability), discrete fluctuations of the signals may occur, potentially resulting in inaccurate gas concentration measurements. To this end, by integrating ML and AI in the intelligent sensing layer, the data-cleaning process can be configured to handle anomalies that appear as signal fluctuations, before the data is used to make predictions.

To explore this challenge, PSD differences relative to the prevalent atmospheric concentration of the targeted gases were measured for a fixed distance of 100 m between the transmitter and receiver. Figure 5 presents the measurements of PSD differences for O_3, SO_2, and CH_4 gases when their expected concentrations vary. The frequency ranges corresponding to each gas was selected by studying the PSD measurements. From Fig. 5, we see a significant difference in the PSD for all concentrations at 0.8424, 1.2951, and 1.4930 THz frequency for O_3, SO_2, and CH_4 gases, respectively. Additionally, as a special case, we notice PSD differences were maximized at another frequency (1.3431 THz) for SO_2 gas. Similarly, we noticed high PSD differences in particular frequencies for other gases considered in this study. This shows that we can apply ML techniques to locate the changes in PSD size to determine the different gas levels at specific frequencies when analyzing the big data collected through the proposed network. In future work, this analysis might be extended to predict a certain gas concentration and localize it using ML Techniques.

Challenges

In this section, we list some challenges associated with the use of THz signals for sensing, and in particular, when deployed onto proposed 6G infrastructure.

Ultra-dense Sensing Signals

Given the spatial dispersion of gases within the environment, an essential requirement is the creation of a THz signal blanket that covers an area with sufficient spatial granularity. To cover specific areas, we could increase infrastructure density, such as passive IRSs and UM-MIMO base stations. Although drones may be able to carry nanonetwork sensing panels, they might not be able to cover an area for a period long enough to sense the changes in the gas concentration. Therefore, protocols that consider the tradeoffs between maximizing spatial coverage and minimizing energy consumption will need to be developed to allow fine-grained spatial sensing. In addition, interference between the beams might occur, especially if the number of simultaneous beams is large. However, this should not cause serious problems because THz beams are deliberately thin due to the utilization of high-gain antennas.

Sensing Frequency Switching

The need to switch between frequencies on a single device, to facilitate communication as well as gas sensing, poses technical challenges. One promising approach is to use a

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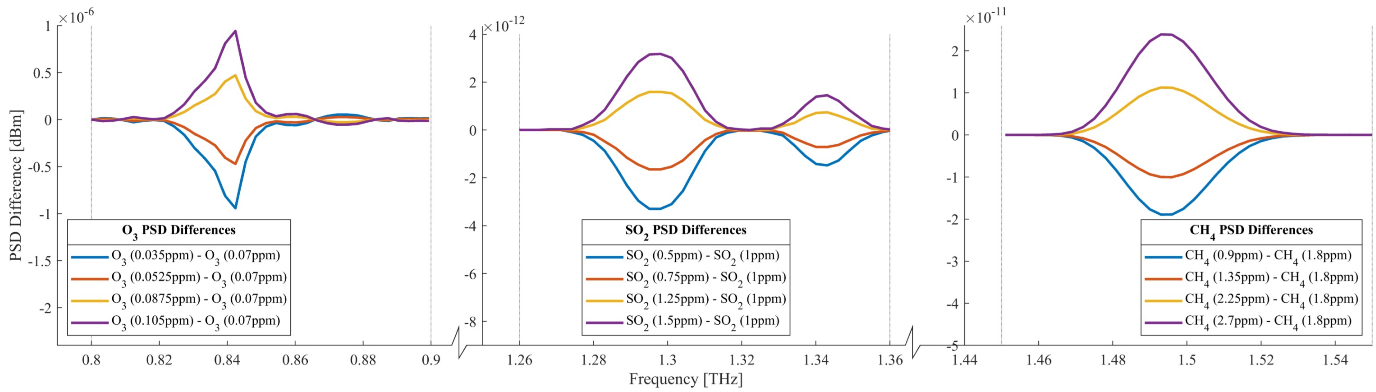

Fig. 5: Comparing PSD difference for ozone, sulfur dioxide, and methane relative to their standard atmospheric concentrations.

multi-band antenna array comprising several nano-antennas working at different frequencies. The frequency of graphene-based antenna strips can be tuned to make this technique possible [4]. However, mutual coupling could pose difficulties when integrating these multi-band antenna arrays because of ultra-dense integration (c.f., ultra-massive MIMO [15]). More research into metamaterials and their integration into such antenna arrays is needed. Since the sensing unit needs to sweep through multiple frequencies, a chirp spread spectrum needs to be generated and analyzed. This provides an opportunity to utilize the large bandwidth in the THz spectrum, normally used for communications, for sensing a wide frequency range.

Reconfigurable Beam to Minimize Sensing Deafness

While (massive) antenna arrays in the THz spectrum can be used to generate pencil-thin beams to overcome the path loss and meet the link budget requirements, different frequency beams and distributions might be needed to meet the sensing requirements. These include a range of beam configurations, from quasi-omnidirectional short-range beams to single and multiple directional beams. Such flexibility results in hardware challenges that will require on-the-fly reconfiguration of the beam shapes.

Gathering Data for Analysis

We propose that path loss as a function of frequency can be used for sensing, but estimating the location of the sensed region remains a challenge. We propose the use of ML to tri-angulate signals from multiple sources. This will lead to a vast quantity of data for training as well as accurate detection. This data analysis is needed because numerous factors can affect the signals and they can be confounded with each other, making accurate measurement difficult. The data analysis can also assist in minimizing the energy consumption from each device. This can be achieved by varying the sleep cycles of the sensing duration in line with changes in the measured gas. Moreover, signal processing of big data collected through the network is computationally expensive and time-consuming. Thus, real-time monitoring of targeted atmospheric gas concentrations will raise significant challenges, such as a) predicting how much data will be collected and needed and b) managing the hardware and other technology requirements for processing data. Furthermore, since the main objective of every network architecture is to provide continuous and reliable connectivity, we propose gathering data for gas sensing during time intervals the channel is not needed for communication. Intermittent sensing is sufficient because local gas concentrations change slowly, and this will reduce the amount of data to analyze. Finally, accurately measuring gas concentrations when H_2O is present is a challenge. H_2O concentration in the atmosphere varies unpredictably due to environmental conditions. Since H_2O molecular absorption loss is much higher than other gases, it is challenging to sense other important gases when the H_2O percentage is high (e.g., exceeds 1 percent). Furthermore, the atmospheric concentrations of some gases used in the study are expected to be very small, so they are difficult to detect, and changes in their concentrations might be even more difficult to estimate.

Conclusion

Early visions for 6G systems agree that new infrastructure will be needed in the next generation of wireless systems, beyond what is currently being deployed for 5G. Such new infrastructure includes IRS, EM-nanonetworks, and increased frequency spectrum in the THz band. In this paper, we have investigated how we can exploit the absorption of THz signals by certain gases as a new sensing capability for 6G communication networks. Through a preliminary analysis, we show how path loss and power spectral density can be used to sense various gas types. While many challenges await the deployment of our proposed approach, we lay the groundwork for research into how newly added functionalities in telecom-munication infrastructure can measure data for climate change sensing.

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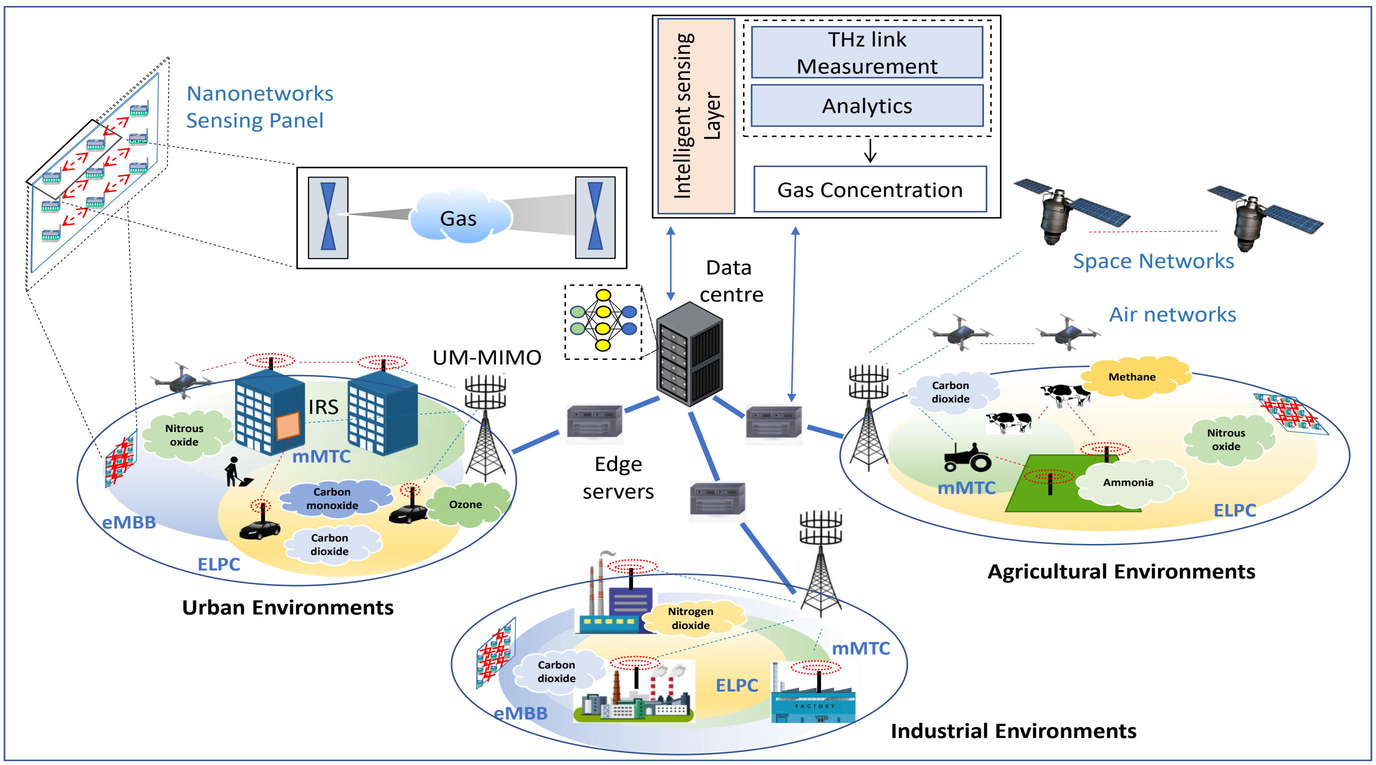

Fig. 6: 6G Network architecture for communication and sensing.

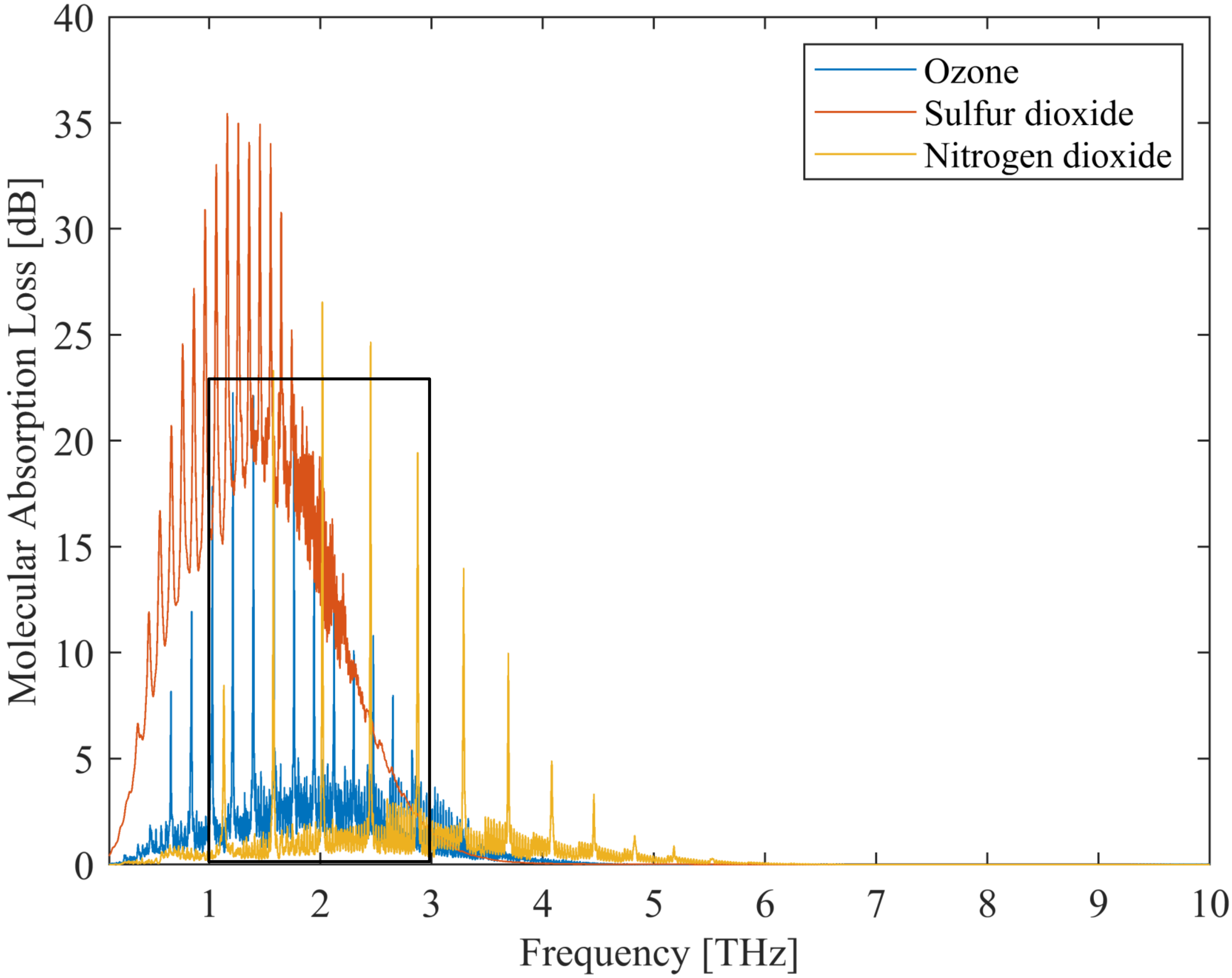

Fig. 7: Simulated molecular absorption losses of THz signals for ozone, sulfur dioxide, and nitrogen dioxide using HITRAN data.

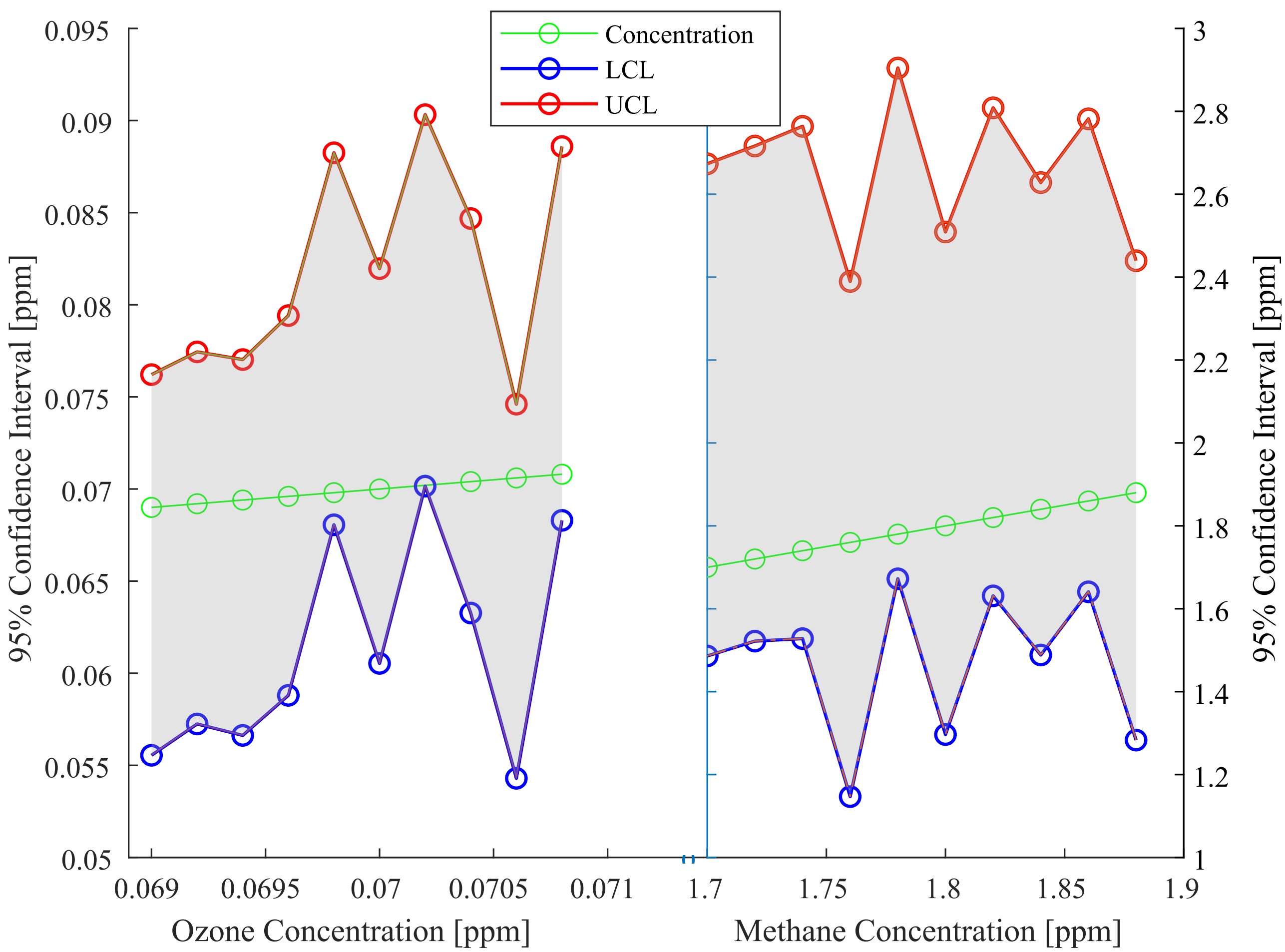

Fig. 8: Measurement sensitivity curve for ozone and methane, showing expected gas concentrations and the confidence intervals (LCL: Lower Confidence Level, UCL: Upper Confidence Level) of the predicted gas concentrations.

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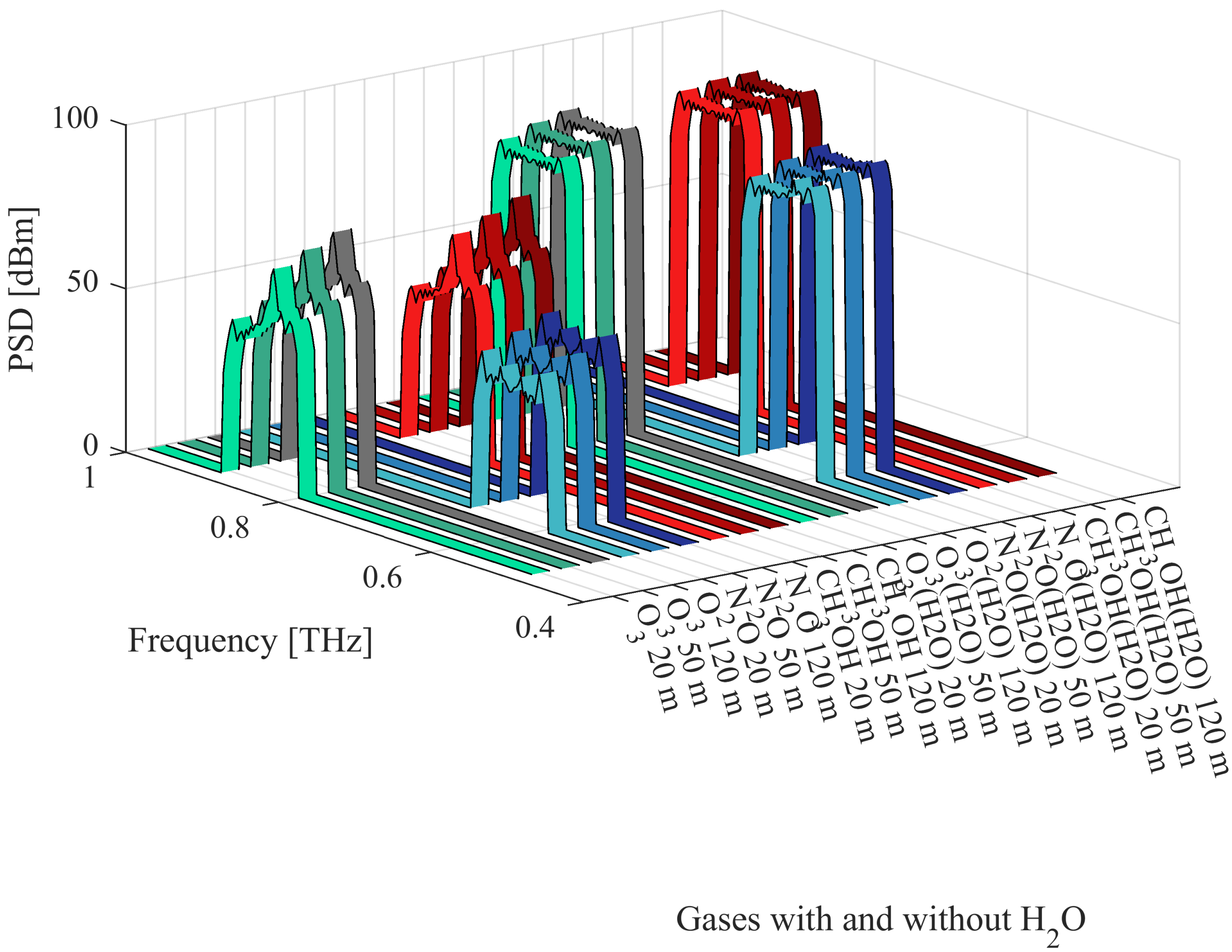

Fig. 9: Total power spectral density for ozone, nitrous oxide, and methanol considering a mixture with and without water vapor and varying distance between transmitter and receiver.

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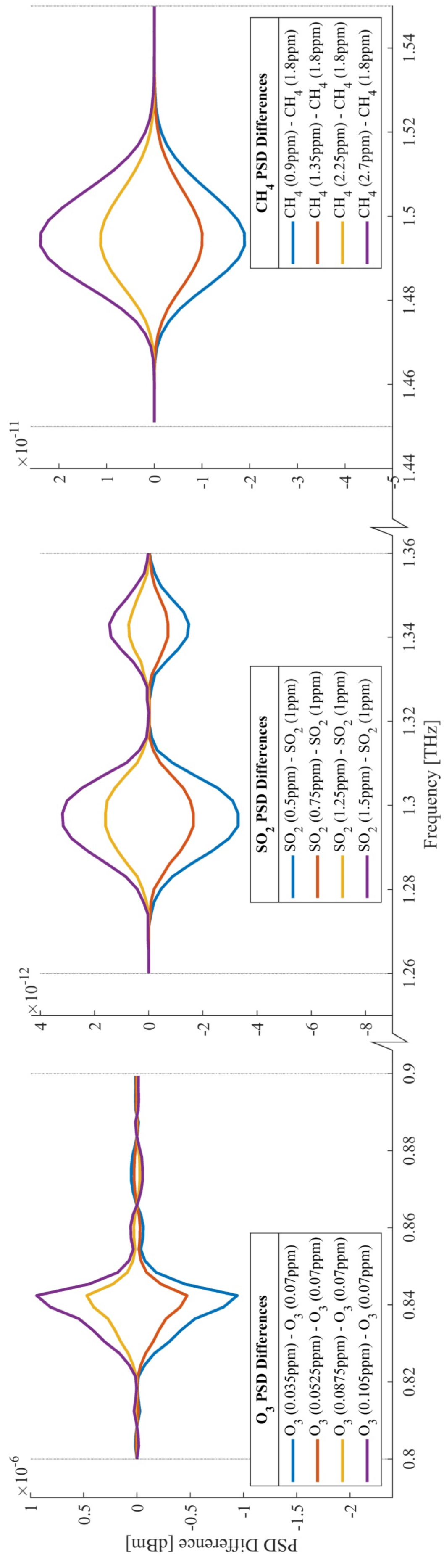

Fig. 10: Comparing PSD difference for ozone, sulfur dioxide, and methane relative to their standard atmospheric concentrations.