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Temperature retrieval in combustions by using multilayer perceptron and feature selection in the CO_2 infrared emission band.

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ABSTRACT

In this work a methodology based on the combined use of a multilayer perceptron model fed by selected spectral information is presented to invert the radiative transfer equation (RTE) and to recover the spatial temperature profile inside a flame. The spectral information is provided by the measurement of the infrared CO_2 emission band in the 3-5 μm spectral region. A guided spectral feature selection has been carried out by using a joint criterion of principal component analysis and "a priori" physical knowledge of the radiative problem. After applying this guided feature selection a subset of only 19 wavenumbers have been selected out of thousand possible. The proposed methodology has been applied over synthetic scenarios. Also an experimental validation has been carried out by measuring with a Fourier-transform based spectroradiometer the spectral emission of the exhaust hot gas plume in a controlled microjet engine. Temperatures retrieved by the proposed methodology have been compared with classical thermocouple measurements, showing a good agreement between them. Results obtained by the proposed methodology are very promising and can encourage the use of sensor systems based on the spectral measurement of the CO_2 emission band in the 3-5 μm spectral window to monitor combustion processes in a non-intrusive way.

Keywords: combustion monitoring, flame temperature, infrared remote sensing, feature selection, multilayer perceptron, principal component analysis.

1. INTRODUCTION

In an industrial fuel-fired furnace, it is very important to have devices that monitor and control the combustion processes. An excess of air or oxygen supplied to the process leads to an increase in the electrical power consumption, significant energy losses and an increase of pollutant emissions associated to highly oxidized by-products like nitrogen dioxide and monoxide (commonly referred as NO_x). Insufficient air or oxygen supply leads to an increase of pollutant by-products associated to bad combustion conditions, like unburned hydrocarbons, carbon monoxide or particulate emissions. Usually, a combustion control system supplies air or oxygen to the furnace based on preconceived melt temperature schemes. Sometimes, manual biasing is possible, based on operator experience and limited periodical monitoring information. However, a smart and automatic control system appears to be the most suitable solution to guarantee the correct monitoring of the combustion. In this context, a reliable automatic monitoring of flames in combustion processes plays an important role in the energy conversion

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efficiency, control of pollutant emissions and basically the optimization of these processes [1-3]

Real flame temperature appears, among others, as a very important parameter to be monitor. Conventional temperature monitoring devices such as thermocouples are intrusive and therefore they disturb the measurement, and they also must undergo the harsh furnace environment. Remote optical measurements are more suitable because they are non-intrusive and they can be used in hazard environments. Ultraviolet, visible and infrared detectors have been used in flame monitoring systems [1,2,4-6]. Infrared sensing appears to be very promising, because the hot gases in the flame, mainly carbon dioxide (CO_2) and water vapour (H_2O) exhibit important emission bands in the infrared region. Fig. 1 shows a typical spectral distribution of the radiance emitted by the flame of a burner. Notice the prominent emission band due to hot CO2 which is centred around 4.4 μm

Two main approaches are usually done to obtain the real flame temperature. One of them uses devices such as pyrometers that integrate the received energy in a wide range of wavelengths. However, the main disadvantage of these instruments is the fact that they are calibrated by using blackbodies, and the radiative properties of a flame are very far away from a blackbody. This drawback is intended to be corrected by using the emissivity, but this factor is not usually known with enough accuracy for flames. Moreover, the flame has strong temperature gradients, and these devices cannot provide the temperature profile. Summarising, flame pyrometry can only provide a measure of brightness temperature integrating all temperature profiles in the field of view of the instrument. The second approach that corrects the previous drawbacks is based on spectrometric measurements that discriminate the received energy as a function of the wavenumber. A recent trend in flame thermometry is to apply the so-called emission-transmission method by using tuneable infrared laser and optical fibre [7]. This technique is an active technique, because it uses an external infrared source. These methods are very sensitive, but their high cost and complexity makes them not very suitable for routine operations in industrial furnaces.

A new methodology for the retrieval of flame temperature profiles is proposed in this work. The method is based on the measurement of the spectral radiance emitted by the hot gases (passive technique).

Retrieval of temperature profiles from the measured spectral radiance requires the inversion of the Radiative Transfer Equation (RTE). This inversion problem is ill-posed since we are trying to recover a continuous function T(x) – being x a point in the optical path inside the flame – from a discrete number of experimental data (the spectral radiance). There are also problems related with the high dimensionality of the data. Therefore, the solution of the inversion problem is not unique, and retrieval codes can obtain, as a result, different temperature profiles for the same input spectrum.

Standard variational approaches to invert the RTE use a forward model, based on physical laws, to calculate the spectral radiance from a given temperature and concentration profiles. These retrieval methods begin with an initial guess for these profiles. Then, they calculate the corresponding radiance spectrum, comparing it with the experimental one. Following an iterative process the initial profiles are adjusted using the difference between the calculated and the experimental spectra until this difference is below a prefixed threshold. The main advantage of these methods is their simplicity. However, the iteration process requires to execute the forward model for each iteration – a high time-consuming process- and it is not feasible for real time control. Other important problem is the strong dependence of the convergence process on the initial guess.

Neural networks (NN) techniques have been used as an approach to solve problems of fitting experimental data. The main goal of this work is to adapt NN techniques to obtain a very promising tool to recover the temperature profile and width of a combustion cloud from its spectral radiance. One important advantage of neural networks over other physical-statistical techniques is their speed. Once the neural network has been trained the inversion method is instantaneous by comparison with the physical iterative models. Other important advantage is that neural networks do not need good initial conditions for the inversion model and do not use direct models to perform the inversion.

This paper presents some demonstrative results within the framework of the authors' proposal to use passive infrared spectroscopy to recover the temperature profile inside a hot gas cloud composed by CO_2 and water vapour, representative of a fossil fuel combustion. The proposal is based on the measurement of the spectral radiance of the CO_2 emission band in the 3-5 μm window. The retrieval model is based on NN analysis over a subset of selected wavenumbers [1] of the measured spectral data.

2. THE PHYSICAL MODEL AND THE DIRECT PROBLEM

For the sake of clarity in the methodology explanation we are dealing in this work only with "clean" flames, where particles are negligible. A modification of these models would be necessary for "dirty" flames in order to take into account radiative transfer of particles, such modification is out of the scope of this work.

The problem to retrieve the temperature profile from the measurement of the spectral radiance is not straightforward in inhomogeneous media. A flame can be represented as a hot gas cloud (mainly composed by CO_2 and H_2O) of a certain length X_F (see Fig. 2). Energy emitted at each wavenumber ν depends in a non-linear way on parameters like the spatial distribution of temperature, gas concentrations and the gas cloud width. Radiance L due to a column of length X_F is given, according to the RTE by

$$L(\nu) = \int_0^{X_F} B[\nu, T(x)] \frac{\partial\, \tau(\nu, x)}{\partial x}\, dx \qquad (1)$$

where $B[\nu,T(x)]$ is the Planck's law and $T(x)$ is the temperature profile inside the gas cloud. Function $\tau(\nu, x)$ gives the transmittance coefficient of the gas column between x and X_F. This function is related (through the well known Beer's law) in a non-linear way with the temperature and gas concentration profiles. This non-linearity is mainly due to the temperature dependence of gas absorption coefficient, the temperature dependence of the Lorentzian pressure-broadening profile and the overlapping of different absorption lines at a given wavenumber. The scheme in Fig. 3 summarizes these effects.

Then, not only the temperature profile $T(x)$ but also the flame length X_F are the physical variables that determine the intensity as well as the spectral shape of the radiance spectrum. The energy emitted at each wavenumber depends in a complex way on both parameters. To illustrate this complexity, Fig. 4 shows a theoretical calculation of the CO_2 emission band for three different situations: a 100 cm wide CO_2 cloud at 1000 K , the same cloud temperature but 1 cm wide and a CO_2 cloud 100 cm wide with an exponentially decaying temperature from 1000 K to 300 K. It is clear from the figure that the shape of the temperature profile and the width of the cloud are key parameters to understand the information involved in the energy emission spectrum.

[1] We want to point out that the words, wavenumbers and features, will be used indistinctly depending upon we are talking from a physical or a machine learning point of view.

3. THE INVERSION OF THE RADIATIVE TRANSFER EQUATION: RETRIEVAL METHODOLOGY.

In order to retrieve T(x) from the radiance spectrum, we propose in this work the use of neural network techniques as an approach to invert the RTE. In the context of approximation of non-linear transformations, the most widely used architecture is the Multilayer Perceptron (MLP). It is a classical and relatively straightforward method to use and it has been proposed by different authors as a universal approximator, in the sense that any continuous function may be represented by a MLP with one hidden layer [8,9]

3.1 Architecture of the MLP

The MLP approximation is composed of three types of layers: input, hidden and output layer. Each layer consists of several neurons which receive their input values in a layer directly below and they send their outputs to the neurons in a layer directly above. The input layer receives the external data and it merely fan-out without any other processing. The activation or output of the other neurons in the network (belonging to the hidden and output layers) is a function of the weighted inputs plus a bias value as follows

$$out_i = f\left(\sum_j w_{ij}x_j + b_i\right) \qquad (2)$$

where x_j, , w_{ij}, and b_i are respectively the inputs, weights and bias associated to the i th neuron. The function f is called the activation function being the sigmoidal function the most used activation function

$$f(x) = \frac{1}{1+e^{-x}} \qquad (3)$$

The output values out_i serve as inputs to the neurons of the next layer and the process is repeated until output values are obtained in the output layer. The values of the activation function for the neurons in the output layer are the final outputs of the MLP.

The training process of the network is the determination of the adjustable parameters—weights and bias—. In this process a dataset of inputs and known outputs are used (supervised learning). Learning rules are generally formulated to move iteratively the adjustable parameters towards values that minimize some particular error function. This error function is usually defined as the difference between the output vector y_k of the MLP and the desired output vector y_k^{des} for the training samples.

$$error = \frac{1}{N}\sum_{k=1}^{N}\left(y_k - y_k^{des}\right)^2 \qquad (4)$$

where N is the number of training samples.

In our case, the input vector is obtained from the spectral radiance. The number of input neurons will be determined by the number of variables (wavenumbers) selected in the spectrum. The output variables are the different temperature values along the hot gas cloud, and the number of hidden neurons is adjusted to obtain the best results.

3.2 Generation of the dataset

For the training phase it is necessary a dataset of spectral radiances representative of the different experimental conditions of the problem under study. This dataset is usually generated by computer codes that simulate the transfer of energy through the hot gas cloud. The energy transfer calculation is based on the Beer's law. Spatial distributions of temperature and gas concentrations inside the cloud are needed as inputs for the code.

A synthetic dataset of radiance spectra has been generated to train the neural network. A computer code developed at Universidad Carlos III (CASIMIR) based on the well known HITRAN/HITEMP spectral database has been used to obtain these spectra [10,11]. CASIMIR has been developed under line-by-line concepts and can calculate radiance spectra at very high spectral resolution. If lower resolution is needed, an smoothing algorithm is used as a post process to simulate the required spectral resolution. The smoothing algorithm simulates the spectral response of the spectroradiometer in order to obtain comparable spectra.

CASIMIR code has been designed to manage inhomogeneous paths in temperature and gas concentrations. The optical path is divided in cells of the same length, being assigned to each one an average value of temperature and gas concentration. Eq. (1) is discretized and solved to calculate the spectral radiance emitted by the gas cloud.

Therefore, CASIMIR needs the spatial temperature and concentration profiles as inputs. In this paper some initial assumptions on these profiles have been introduced in the model. Axial symmetry is assumed for the temperature profile inside the cloud. For a given depth x inside the cloud, the temperature profile along the X direction has always a maximum value at the centre of the cloud (x=0) being symmetric along this direction – T(x)=T(-x) – . A parametric sigmoid function has been used to generate very different shapes of the profile

$$T(x) = T_0 + \frac{(T_1 - T_0)}{1 + e^{\frac{(x - x_0)}{r}}} \qquad (5)$$

where T_0 and T_1 defines the minimum and maximum temperatures into the cloud, x_0 the distance from which the temperature begins to decrease and r the rate of this decrease. Fig. 5 shows some examples of normalized temperature profiles calculated from Eq. (5) and used for the generation of the data set. Values of T_1 range from 600 K to 1200 K and values of width X_F vary from 0.1 m to 2 m. T_0 is fixed to the ambient temperature. These values have been selected to cover a wide range of combustion cases.

The concentration profiles can not be freely generated in the context of this combustion problem, because gas concentrations and temperatures inside an exhaust plume are related. Reference [12] presents a set of equations for the dilution of an aircraft exhaust plume. Following these equations we can found a relationship between the temperature difference plume-ambient air and the change in the volume concentration of a gaseous specie. This relationship involves the emission index of the specie, the specific heat capacity of the plume gases at constant pressure, the effective heat release per unit fuel mass and the molar masses of air and the gaseous specie. From the numerical values obtained from this reference, we have found a numerical equation that relates the differences of temperature ΔT and changes of CO_2 concentration Δc_{CO2} inside the plume

$$\Delta c_{CO2} = 6.9 \times 10^{-5} \Delta T \qquad (6)$$

Taking into account all the above mentioned considerations, the generation of the training dataset has been performed under these conditions:

a) Synthetic spectra will correspond to the spectral distribution of the radiance emitted by a hot gas cloud (CO_2 and H_2O) of width X_F. Temperature and gas concentrations present gradients inside the cloud.
b) The spectral range selected for the simulations is 2110-2410 cm^{-1}. Most of the commercial infrared instruments have capabilities to measure in this range. As can be seen in Fig. 1 the CO_2 emission band is by far the most important emission feature, being the water emission nearly negligible. Due to this fact, only emission associated to the carbon dioxide will be considered in the calculations.
c) This cloud will be spatially divided in basic cells of equal length. Each of the basic cell has an average value of temperature and CO_2 concentration. These average values are calculated from Eqs (5) and (6).
d) The cells with the average values are used to define an inhomogeneous path that constitutes the input of the CASIMIR code. The output of the code would be the spectral distribution of radiance expressed in W /(cm^2sr cm^{-1}).
e) The calculated spectra are smoothed to simulate a spectral resolution of 4 cm^{-1}. This value would be the experimental resolution of the spectroradiometer used to evaluate the goodness of the retrieval algorithm proposed in this work (see section 4) and is very common in commercial instruments.
f) Experimental noise of spectra has not been simulated to avoid analysis features associated to it. In this way the MLP information will be directly related to the temperature profile and width X_F of the gas cloud.
g) The absorption effects, due to the atmospheric CO_2 which is in the path between the gas cloud and the sensor, are included in the synthetic spectra.

3.3 Dimensionality reduction: a spectral feature selection approach.

Progress in optoelectronic technologies during last decade has led to the fabrication of new sensors focused on new measurement concepts based on high spectral resolution capabilities. High resolution measurements can lead to a better understanding of the physical properties related to the radiated energy. However, the amount of information increases in such a way that makes difficult the use of conventional data regression techniques to retrieve the physical information involved in the problem. Many problems usually arise in these kinds of retrievals, related to data dimension or associated to the complexity of regression models and the consequent huge number of operations to solve them.

Within the framework of the proposed MLP model, it is straightforward to think that the more data used in the training phase the better results would be expected in the retrieval algorithm. However, it has been reported that a high data dimensionality lead to a problem called "the curse of dimensionality" [13] which stands that, in practice, we could find a certain point beyond which the addition of new features can actually lead to a reduction in the performance of the machine learning system.

Then, it is needed to find a reduction of dimensionality, from the original high-dimensional space to a low-dimensional one, retaining as much significant information as possible that could be useful for the retrieval purpose. There are different ways to make this reduction of dimensionality that can be classified mainly in two types: feature extraction and feature selection [14]. Feature extraction techniques create a subspace of new variables that can be constructed from the original ones. A typical way to do that is by using Principal Component Analysis (PCA) [15]. On the other hand, feature selection techniques are based on the selection of a subset of the original features. In this work we have adopted a mixed methodology. The feature selection approach has been chosen because it allows to find a subset of original wavenumbers which can be interpreted, and

this interpretation could be focused to the design of specific sensors. On the other hand, a PCA-based analysis has been adopted to make the selection of these wavenumbers which have the most significant physical information.

PCA is a multivariate statistical analysis, commonly used, among others, in hyperspectral remote sensing techniques, that transforms a number of correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. In this way, the dimensionality of the problem is reduced by eliminating the correlated variables and retaining as much as possible the variation in the original dataset [15]. With this reduction of the input dimension the performance of the MLP is greatly improved, avoiding the problems related to the high–dimensionality of the original data.

As it was pointed above, PCA will not be used in this work in a standard way, extracting a new feature subset from the original dataset. Instead of that, PCA has been used as a tool to achieve a guided spectral feature selection jointly with an introduction of a-priori specific knowledge of the physical problem we are working on.

3.4 Guided feature selection and MLP training

The proposed guided feature selection is based on the structure of the eigenvectors obtained by a PC analysis, and the knowledge of that adjacent wavenumbers carries similar physical information.

PCA is a lineal dimensionality reduction technique that tries to preserve the variability of a dataset. Given an input dataset $S = \{s_1^M, s_2^M, \dots, s_n^M\}$, composed by *n* radiance spectra of M variables (wavenumbers), let B be the principal component matrix that is obtained from the diagonalization of its covariance matrix. Usually, in high dimensional data there exists a lower subspace, or a subset m of original variables (m << M) that contains most of the information available in these M variables. It is common to use the projection of the original data over the new basis B obtained by PCA as new features (feature transformation approach). In this work an alternative procedure is used based on the analysis of the structure of the eigenvector coefficients to find those features which best preserve the variability. Therefore we look for those coefficients which have the highest absolute value for the first eigenvectors. This criterion is based on the fact that high values for the coefficients mean that the features associated to these values have a stronger influence from a statistical point of view.

In order to choose a number of principal components that can account for most of the variability in the dataset, it is necessary to check the accumulated percentage of variance for the dataset. If the spectrum s_i^M can be successfully described by only m PCs, then it will often be true that the dimension M can be replaced by a subset of m variables with a small loss of information [15]. Table 1 shows this percentage taking into account different number of succeeding principal components. From this table it is obtained that the choice of the first 5 or 6 principal components lead to a recovering of around 99.9% of the total variation in the dataset.

In order to improve the selection process, we have added a constraint, which makes use of specific physical knowledge, to modify the proposed method based on the eigenvectors coefficients. The information related to the physics of the problem has been extracted from the analysis of the weighting functions in the RTE equation. The weighting function is the term related with the partial derivative of the transmittance function in Eq. (1), and gives information (for each wavenumber) about how important is the radiance coming from a certain depth inside the flame. A study of these weighting functions has been performed for the dataset described in section 3.2. From this study the main conclusion for our purposes is that adjacent wavenumbers contains information from

very similar depths inside the flame. This result can be introduced as a constraint in the feature selection process. This constraint forces to choose not only the coefficient with the highest value, but also other coefficients with high values that correspond to different wavenumbers, not to close between them, and which can scan the complete spectral region. In this way, we have selected those wavenumbers that are not only statistically relevant but furthermore related to different areas of the profile that we want to retrieve.

In this paper we have taken a conservative stance in a sense of not trying to find the optimum number for the variable reduction but seeing how the reduction improves the performance of the MLP model. In this sense feature selection based on a joint criteria of PCA analysis and physical knowledge has been used to select a reduced (but not minimum) number of wavenumbers. The criterion to select the subset of original variables has been the choice of those wavenumbers for which the related eigenspectrum coefficients reach local maxima or minima values in order to take the most relevant information of each eigenspectrum. Fig. 6 illustrates this spectral selection over the first 5 eigenspectra.

Table 2 summarizes the results obtained for the temperature profile retrieval by using the MLP model trained and tested with the synthetic dataset. Two cases have been studied. In the first one the whole spectrum variables (M=247) have been used as inputs of the MLP. In the second one, only the reduced subset of variables (m=19) has been used. In both cases, different architectures with different number of hidden neurons have been used. The performance of the retrieval model is compared by using the mean temperature error calculated by Eq. (4). These results show that the use of the reduced dataset improves the retrieval results for all the architectures. Other fact that has been observed is that overfitting of the MLP occurs early during the training phase for architectures with 30 and 40 hidden neurons when the whole set of variables is used. This means that due to high dimensionality of the inputs, the MLP overfits quickly to the training data losing its general predictive behaviour. For the reduced subset of variables, overfitting is not observed for any architecture. In this last case, a selection of 30 hidden neurons gives the best results.

Summarizing, the combination of MLP (with an architecture of 30 hidden neurons) and a feature selection based on PCA appears to be a very good tool to retrieve temperature profiles in flames using infrared multispectral sensors.

4. EXPERIMENTAL VALIDATION AND DICUSSION ON THE RESULTS

In order to check the ability of the proposed methodology to retrieve temperature profiles experimental measurement of the radiance spectra emitted by the gas exhaust of a microjet engine has been performed. The microjet turbine was atypical engine used for aeromodelling, with a thrust of around 100 N. The engine was placed in a measurement bench. A particular nozzle with a shape of truncated cone has been added to the turbine in order to shield the strong IR emission due to the hot metallic parts of the engine.

The optical sensor to measure the radiance spectra was an Fourier Transform-based FTIR spectroradiometer (model MIDAC-AM).The spectroradiometer is equipped with a mercury-cadmium-telluride (MCT) detector, and measures the spectral radiance between 600-4500 cm^{-1} ($\approx$ 2.2-16.7 μm). This instrument has been previously calibrated to radiometric units W / (cm^2 sr cm^{-1}) by using a laboratory blackbody at different temperatures. Due to the fact that spectral resolution and time acquisition are related in a FTIR spectroradiometer, a moderate resolution of 4 cm^{-1} has been selected to carry out the measurements. This resolution is high enough to measure the CO_2 emission band and otherwise allows for having acquisition times as short as 100 milliseconds for each spectrum.

A black screen is located behind the exhaust gas plume to avoid the measurement of undesired IR reflections. In order to measure a radiance spectrum it is mandatory to know the value of the emitter surface. The definition of an emitter surface is not a straightforward task when the emitter is a tri-dimensional gas volume with important temperature gradients (instead of a typical uniform flat solid surface). The spectroradiometer field of view has an angle of around 24 mrad and this value is too high to define in a precise way the surface of the emitter. Then, it is necessary to insert between the exhaust plume and the spectroradiometer a black screen with a small circular aperture to define in a precise way the emitter surface. This screen must be placed as close as possible to the gas plume but keeping a gap to avoid its heating. The diameter of the aperture must be small enough to allow a useful calculation of the radiance spectrum, but not too small because in that case the energy level at the spectroradiometer input would be very low. An optimum value to counterbalance both aspects is a diameter of 1 cm.

Fig. 7 summarizes the experimental setup. As can be seen in the figure, the spectroradiometer is placed in such a way that its optical axis is perpendicular to the symmetry axis of the plume.

In order to study the stability of the infrared emission of the plume, five spectra have been measured in the same experimental conditions. These spectra have been measured on a point located on the axis at 2 cm from the nozzle exhaust. Fig. 8 shows that the emission is very stable. This result validates the choice of the spectral resolution of 4 cm^{-1} as a value that guarantees both short acquisition times and stability in the measured spectra.

Once the experimental spectrum is acquired, these steps must be followed

a) A background spectrum, measured when the engine is off, is subtracted from the measured spectrum.

b) An atmospheric correction is performed in order to remove the absorption feature due to the atmospheric (cold) CO_2 in the optical path between the emitter and the sensor.

c) The calibration algorithm is applied to obtain radiometric units.

d) A smoothing algorithm is applied to avoid as much as possible the effects of the experimental noise in the MLP analysis.

Once this procedure is performed, the values of the radiance at the selected wavenumbers feed the MLP model as inputs. Fig. 9 illustrates the results obtained for the retrieved temperature profile. These results have been compared with thermocouple measurements carried out during the repetition of the experiment, performed for validation purposes only. This repetition of the experiment has been done trying to repeat all parameters as tightly as possible, mainly the regime of the turbine. For clarity purposes only the profile from the center of the plume is represented, assuming axial symmetry. The obtained results are very promising as can be seen from the figure. The temperature at the plume center (mostly the most important temperature for monitoring purposes) has been recovered with only a difference around 1.5% comparing with the thermocouple measurement. For lower temperatures, the trend of the profile is well reproduced, although the differences relative to the spatial distribution of retrieved temperatures become higher. For instance if we choose the temperature of 600 K to estimate the width of the plume, differences of 15% have been found between the width calculated from the MLP retrieval and the calculated one from the thermocouple measurements.

The differences observed respect to the TC measurements are the expected. In fact, for one side, thermocouple data was not obtained simultaneously to the infrared spectroradiometer measurements as it would be spoiled them for the sake of quenching and reemission effects of the metal forming TCs. Although both type of measurements, spectral and TC, has been done repeating as much as possible the same circumstances (rpm regime in the turbine), some little differences in temperature, gases in the room, position of TC respect to the coordinates of the retrieval, etc., must have arisen inadvertently during the experimental process. Taking into account the considerations cited before about the circumstances of TC measurement and the obtained results, it can be concluded that the proposed method has been validated for clean flames and is a firm candidate for the industrial use in non contact retrieval of temperature and position (mapping) of gas combustions plumes.

The extension of the proposed method to the remote sensing of gas clouds will be possible after the inclusion of effects due to particles and spectral noise. Moreover this method opens the door to the research and development of other powerful and interesting procedures of remote sensing involving hyper and multispectral imaging.

5. CONCLUSIONS

Inversion of the RTE to retrieve physical information from the spectral emission of a flame (i.e. a hot gas cloud) is not a straightforward question. It is a non-linear, ill-posed and high dimensional problem. In this paper a methodology based in the combined use of a multilayer perceptron model fed by selected spectral information is presented. A guided spectral feature selection has been carried out by using a joint criterion of principal component analysis and a-priori physical knowledge. These feature selection is done over the spectral emission band of CO_2 centered at around 4.4 μm.

This approach presents important advantages over the classical physical-statistical techniques as higher speed, autonomy of initial conditions and adaptability to other environments, what makes it very suitable for industrial applications. After applying our guided feature selection, a final subset of only 19 wavenumbers has been selected. A conservative stance has been followed to show that an appropriate feature selection method improves greatly the performance of the retrieval. The proposed methodology has recovered the flame temperature profile with high accuracy when applied over synthetic scenarios. Moreover, the extension of this methodology would allow the design of specific multispectral sensors with a low number of channels.

Experimental validation has been carried out by measuring the spectral emission of the exhaust hot gas plume in a microjet engine. The experimental spectrum has been analyzed with the proposed methodology and the temperature profile obtained by the MLP has been compared with thermocouple measurements. The agreement between the retrieved and measured temperatures is very good in general: Temperature differences between the MLP retrieval and the thermocouple measurements are around 1.5% for the center of the plume (highest temperatures). From the spatial point of view a slight mismatch has been obtained comparing the MLP retrieval and thermocouple values. Taking 600 K as a reference temperature, differences in the width plume has been estimated around 15% between the MLP retrieval and the thermocouple measurements.

Results obtained by the proposed methodology are very promising and can encourage the use of sensor systems based on the spectral measurement of the CO_2 emission band in the 3-5 μm spectral window to monitor in a non intrusive way combustion processes.

Moreover, the extension of the propose method opens the door, after optimization, to the remote sensing of gas clouds and the development of other powerful and interesting

procedures of real time remote sensing based on hyper and multispectral infrared imaging.

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FIGURE CAPTIONS

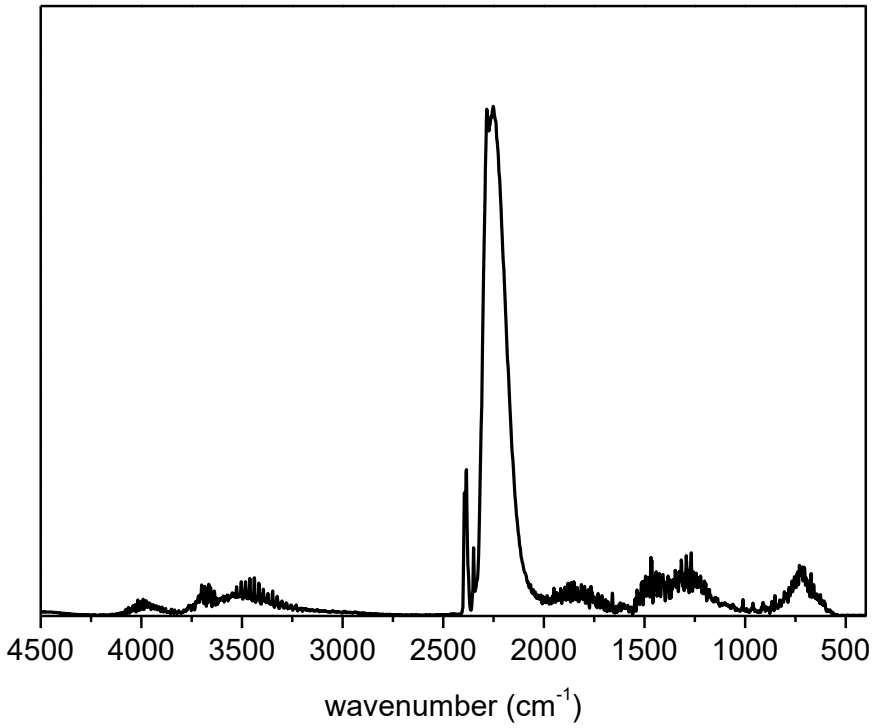

Figure 1: Experimental radiance spectrum of a flame measured in the 400-4500 cm^{-1} spectral region with a spectral resolution of 4 cm^{-1}. Main emission features are due to the CO_2 and H_2O produced during the combustion. Limits of the 3-5 µm atmospheric window are indicated.

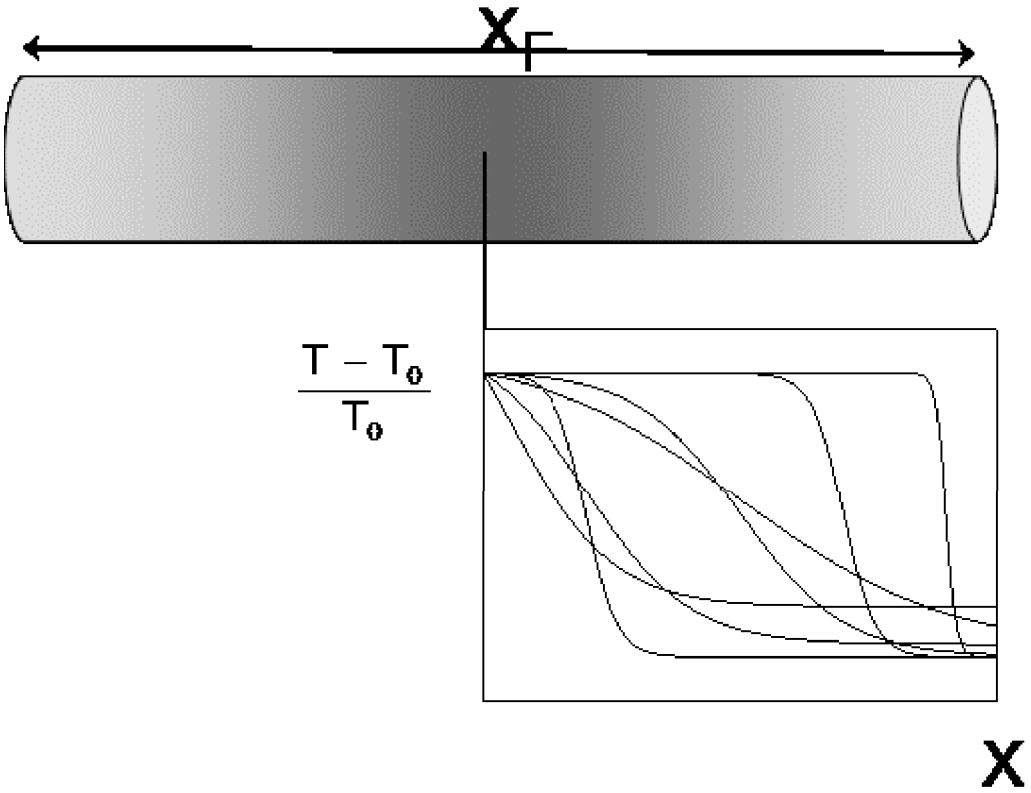

Figure 2: Examples of nomalized temperature profiles inside the gas cloud generated by using Eq. (5). Due to the symmetry of the problem only the half part of the profile is represented.

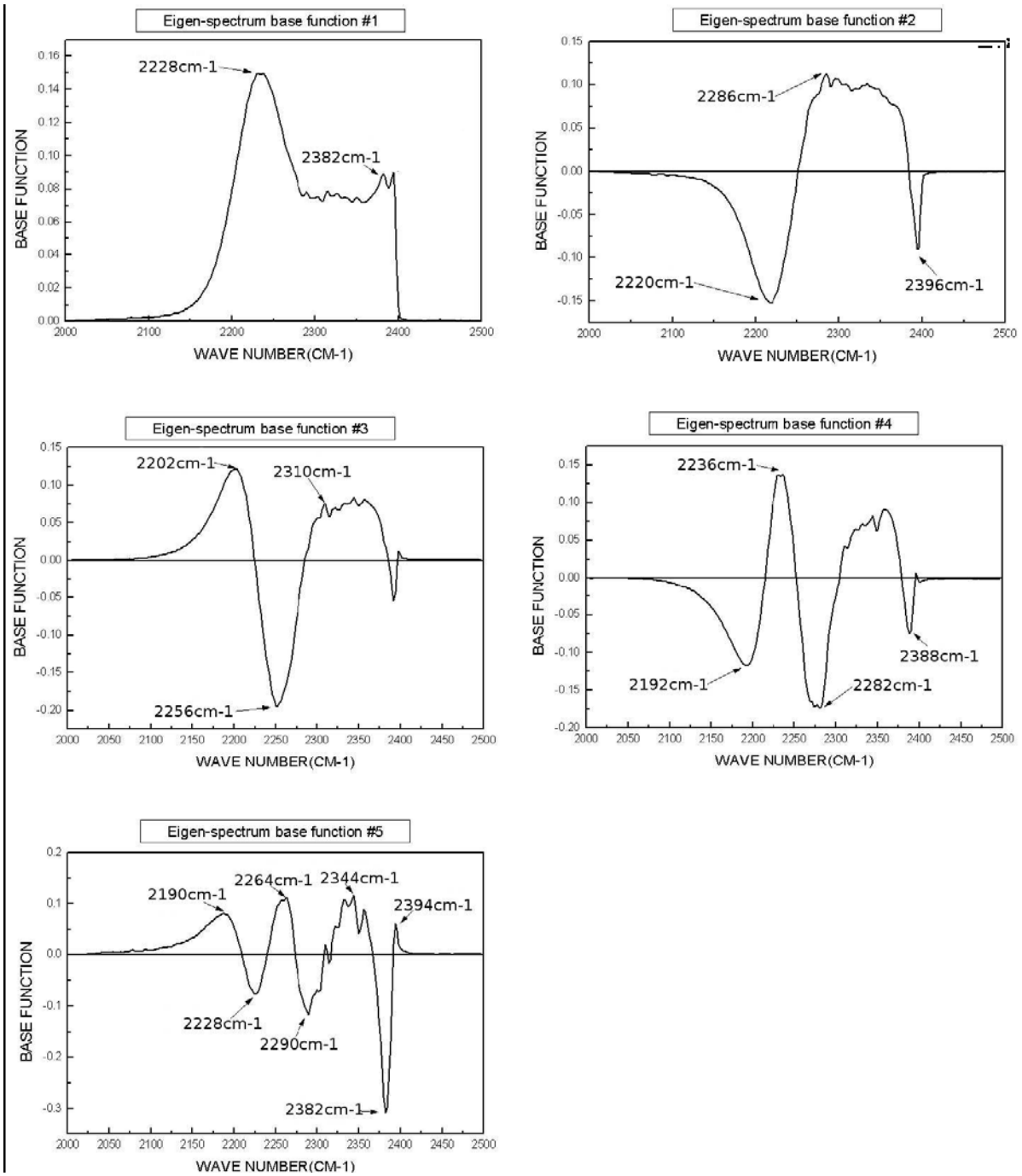

Figure 3: Illustration of the first 6 eigenspectra (PC) with the wavenumbers selected for the spectral feature selection and reduction of dimensionality.

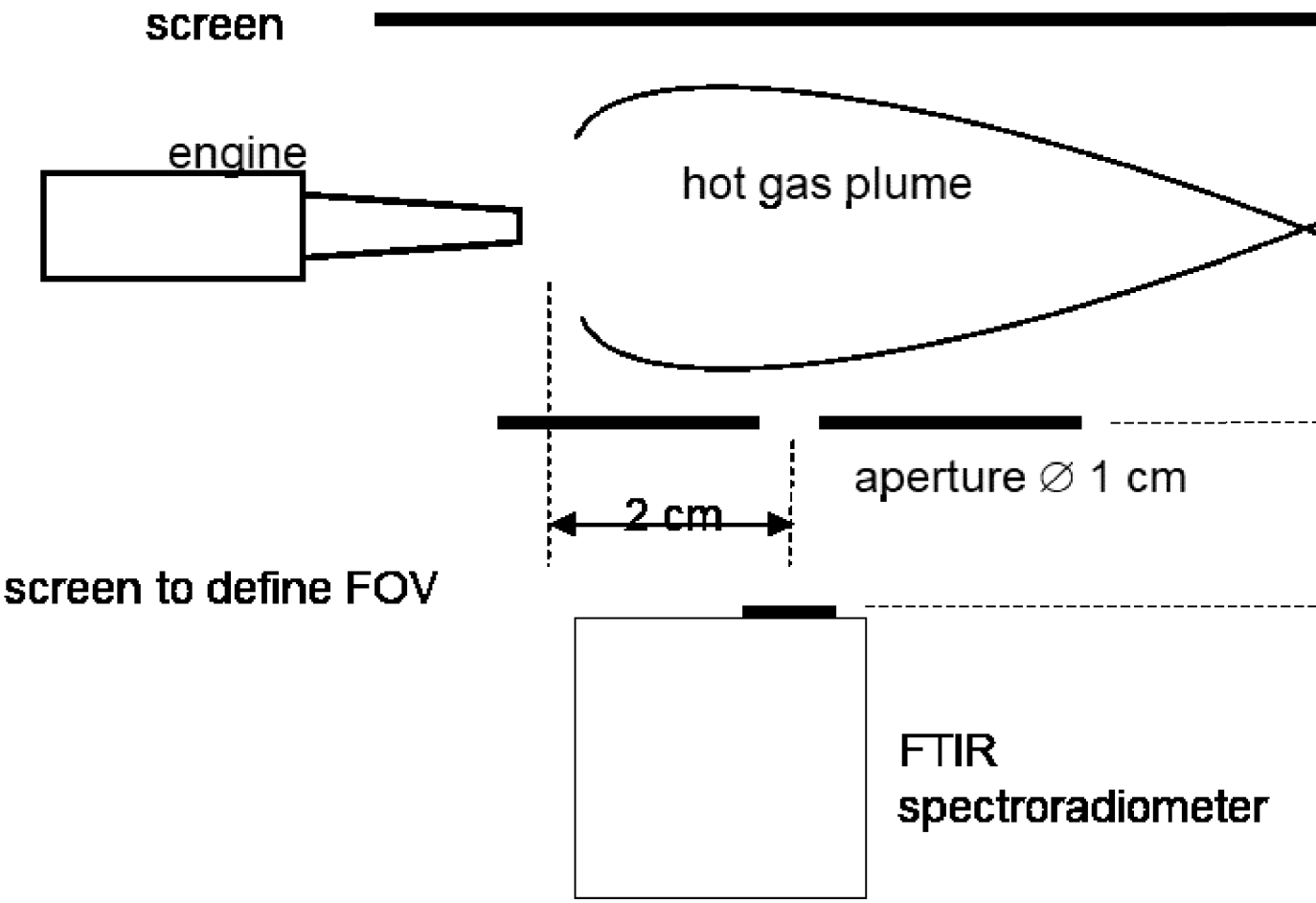

Figure 4: Scheme of the experimental setup used to measure the spectral radiace emitted by the exhaust gas plume of a microjet engine.

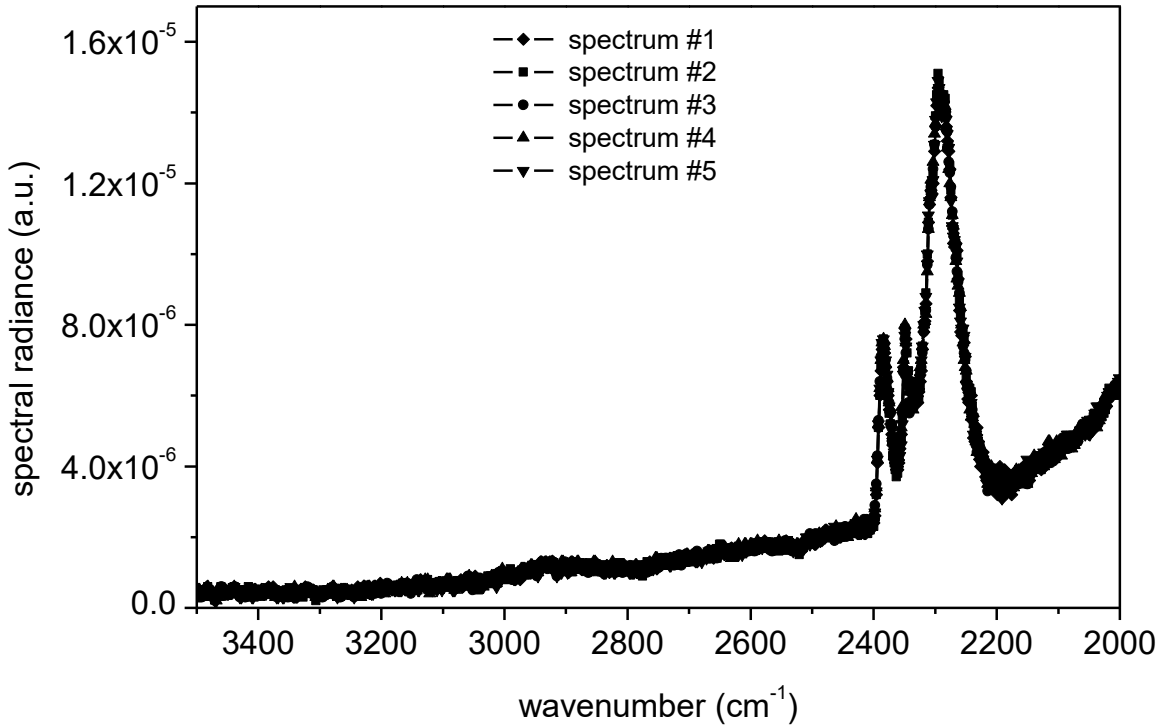

Figure 5: Set of five spectra measured at the same experimental conditions.

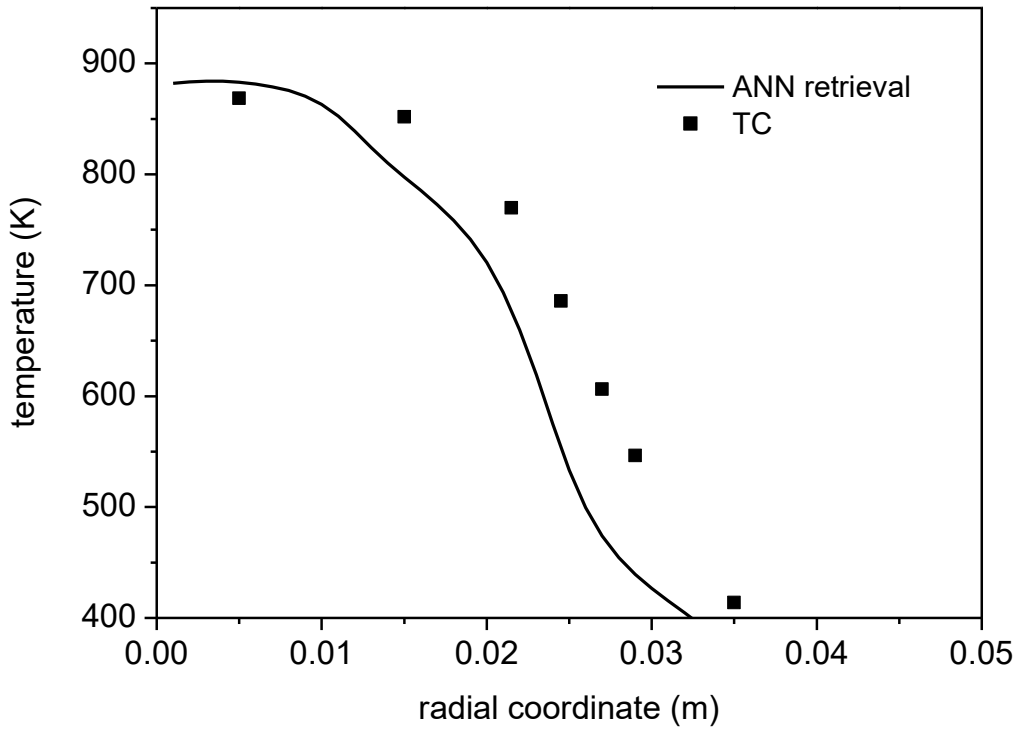

Figure 6: Temperature profile retrieved from the MLP analysis compared with thermocouple measurements. The temperature profile is obtained for the radial coordinate at a distance of 2 cm from the nozzle exhaust.

TABLE CAPTIONS

Table 1: Accumulated percentage of variance for the generated spectra dataset

Number of Principal Components	Accumulated variance (%)
1	88.58
2	97.05
3	99.46
4	99.81
5	99.88
6	99.94
7	99.97
8	99.98
9	99.98
10	99.98

Table 2: Errors in the temperature profile retrieval for different MLP architectures. Two input datasets has been considered: the whole dataset of variables and the reduced subset obtained from PCA

Hidden neurons	Mean error (K) (whole spectrum)	Mean error (K) (feature selection)
10	22.4	17.1
20	7.7	6.5
30	7.4	5.4
40	7.9	6.9