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Machine learning for integrating combustion chemistry in numerical simulations

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Abstract

A strategy based on machine learning is discussed to close the gap between the detailed description of combustion chemistry and the numerical simulation of combustion systems. Indeed, the partial differential equations describing chemical kinetics are stiff and involve many degrees of freedom, making their solving in three-dimensional unsteady simulations very challenging. It is discussed in this work how a reduction of the computing cost by an order of magnitude can be achieved using a set of neural networks trained for solving chemistry. The thermochemical database used for training is composed of time evolutions of stochastic particles carrying chemical species mass fractions and temperature according to a turbulent micro-mixing problem coupled with complex chemistry. The novelty of the work lies in the decomposition of the thermochemical hyperspace into clusters to facilitate the training of neural networks. This decomposition is performed with the Kmeans algorithm, a local principal component analysis is then applied to every cluster. This new methodology for combustion chemistry reduction is tested under conditions representative of a non-premixed syngas oxy-flame.

Keywords: Combustion chemistry, Micro-mixing modeling, Principal component analysis, Artificial neural network, Chemistry reduction

1. Introduction

2 Despite of the continuous progress in supercomputing methodologies, all the degrees of free-
3 dom required to fully describe the detail of combustion chemistry cannot be introduced in the nu-

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4 merical simulations of large-scale combustion systems, such as boilers and furnaces. Several meth-
5 ods have been proposed in the literature to reduce and optimize large chemical kinetic schemes,
6 such as Quasi-Steady State Approximation (QSSA) and partial equilibrium [1], Directed Rela-
7 tion Graph (DRG) [2], Directed Relation Graph with error propagation [3], DRG-aided sensitivity
8 analysis (DRGASA) [4] or again unimportant reaction elimination [5] (not exhaustive list).

9 Even after reducing the number of differential equations solved, because of the very stiff char-
10 acter of differential systems associated to combustion chemistry, the CPU time devoted to their
11 integration remains quite significant and in most cases, too large to allow for performing the mul-
12 tiple simulations needed to complete the quest of the optimal design for a combustion system.

13 These computing limitations motivated the introduction of artificial neural networks (ANN) to
14 deal with chemistry reduction and its time integration [6] and also to develop data driven turbulent
15 combustion modeling [7], or to analyse experimental measurements [8] and to setup digital-twins
16 for process control [9].

17 Among these works, ANN and convolutional neural networks (CNN) were trained on a repre-
18 sentative dataset to replace chemistry integration [10] and the method was applied to perform direct
19 numerical simulation (DNS) of a syngas oxy-flame. Nevertheless, the training of the full dataset
20 using a single or two ANNs required specific treatments, such as data augmentation through man-
21 ufactured intermediate solution points for dealing with some fast reacting species [10]. These
22 operations requiring fine tuning by the user were found necessary to secure good accuracy over
23 the whole domain covering from chemically frozen-flow mixing up to the equilibrium state and
24 pollutant emissions, with fast ignition and fuel oxidation in between.

25 To avoid relying on these additional more or less ad-hoc operations, thus allowing for having
26 a computerised and fully automatic procedure, a novel method is proposed in the present study
27 for turbulent non-premixed flames in which techniques such as data clustering with K-means [11]
28 and dimension reduction using LPCA [12], are combined with ANN training to secure, by con-
29 struction, accuracy over the entire composition space domain (mixing, ignition, combustion and
30 equilibrium state).

31 The paper is organised as follow, in the subsequent section the operating conditions considered
32 and the novel methodology proposed are discussed. After that, the obtained ANN is tested in a

33 posteriori manner for chemistry integration, to study the robustness of the method and the CPU
34 time reduction.

35 **2. Chemistry integration with machine learning**

36 *2.1. Thermochemical conditions*

37 The operating condition considered in this study is taken from previous works on syngas, with
38 a chemical composition representative of those found in the steel industry in recycled exhaust
39 gases [13]. This non-premixed syngas oxy-flame operates under a pressure of 341.3kPa, with the
40 two inlets: (i) syngas fuel injected at 1223K for a mass flow rate of 0.74kg/s and the composition
41 in mass fraction H₂: 0.0085, CO: 0.7852, CO₂: 0.0514, N₂: 0.1549; (ii) pure oxygen at 298K with
42 a mass flow rate of 0.69kg/s.

43 *2.2. Database generation*

44 A database of chemical evolutions is first generated by solving for the mass fractions and the
45 enthalpy of a set stochastic particles featuring at initial condition the concentration in the fuel or
46 in the oxidizer inlet. Then, the species mass fraction $Y_i^p(t)$ and sensible enthalpy $h_s^p(t)$ of each
47 stochastic particle evolve according to the following equations:

$$\frac{dY_i^p(t)}{dt} = \text{MIX}_i^p(\tau_T) + \dot{\omega}_i^p, \quad (1)$$

$$\frac{dh_s^p(t)}{dt} = \text{MIX}_{h_s}^p(\tau_T) + \dot{\omega}_{h_s}^p, \quad (2)$$

48 where ‘MIX’ denotes the stochastic turbulent micro-mixing closure for the diffusive budget in
49 a non-premixed system. τ_T denotes the micro-mixing time and $\dot{\omega}_i^p$ and $\dot{\omega}_{h_s}^p$ are the species and
50 enthalpy chemical sources, respectively. In the present study, the Euclidean minimum spanning
51 tree (EMST) micro-mixing model [14] is used to model the turbulent micro-mixing.

52 This approach to generate thermochemical conditions representative of those observed in a real
53 system for studying its chemical response, without explicitly solving for the flow, has been shown
54 effective for partial oxidation of natural gas [15], aircraft engines combustion chambers [16], large-

55 scale furnaces with urea DeNO_x automated control [17], micro- and meso-scale combustion sys-
56 tems [18] and also to build the database for machine learning application to sooting flames [19].

57 Here a total number of 1429 stochastic particles is employed with 740 particles (corresponding
58 to the mass flow rate of 0.74kg/s) assigned to Fuel inlet and 689 particles (corresponding to the
59 mass flow rate of 0.69kg/s) to O₂ inlet.

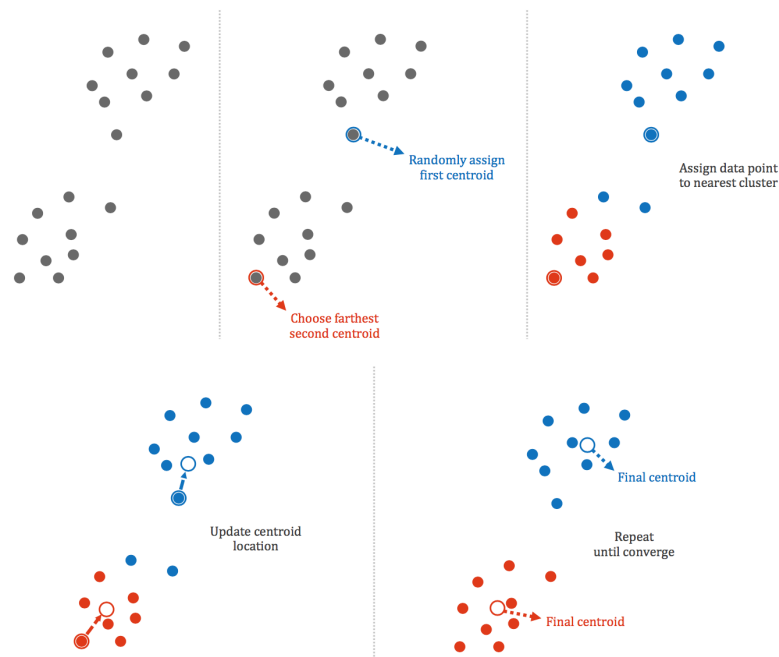


Figure 1: Clustering with K-means

60 From the evolution of these particles, the first step consists of identifying, from a detailed
61 chemical scheme, the important species to be retained and whose evolutions shall be learned by the
62 ANNs. This is done using the direct relation graph with error propagation method (DRGEP) [3].
63 For the present operating conditions, this step was previously performed and reported in [10].
64 Starting from the detailed scheme GRI3.0 [20], 11 species were identified as essential to follow
65 the dynamics of the syngas chemical evolutions: O, O₂, H, H₂, OH, HO₂, H₂O, H₂O₂, CO, CO₂
66 and N₂. A companion reduced chemistry involving 23 reactions was then optimised (see Table 2
67 of [13]).

68 To save CPU time during training and to demonstrate the integration of chemistry with ANN,

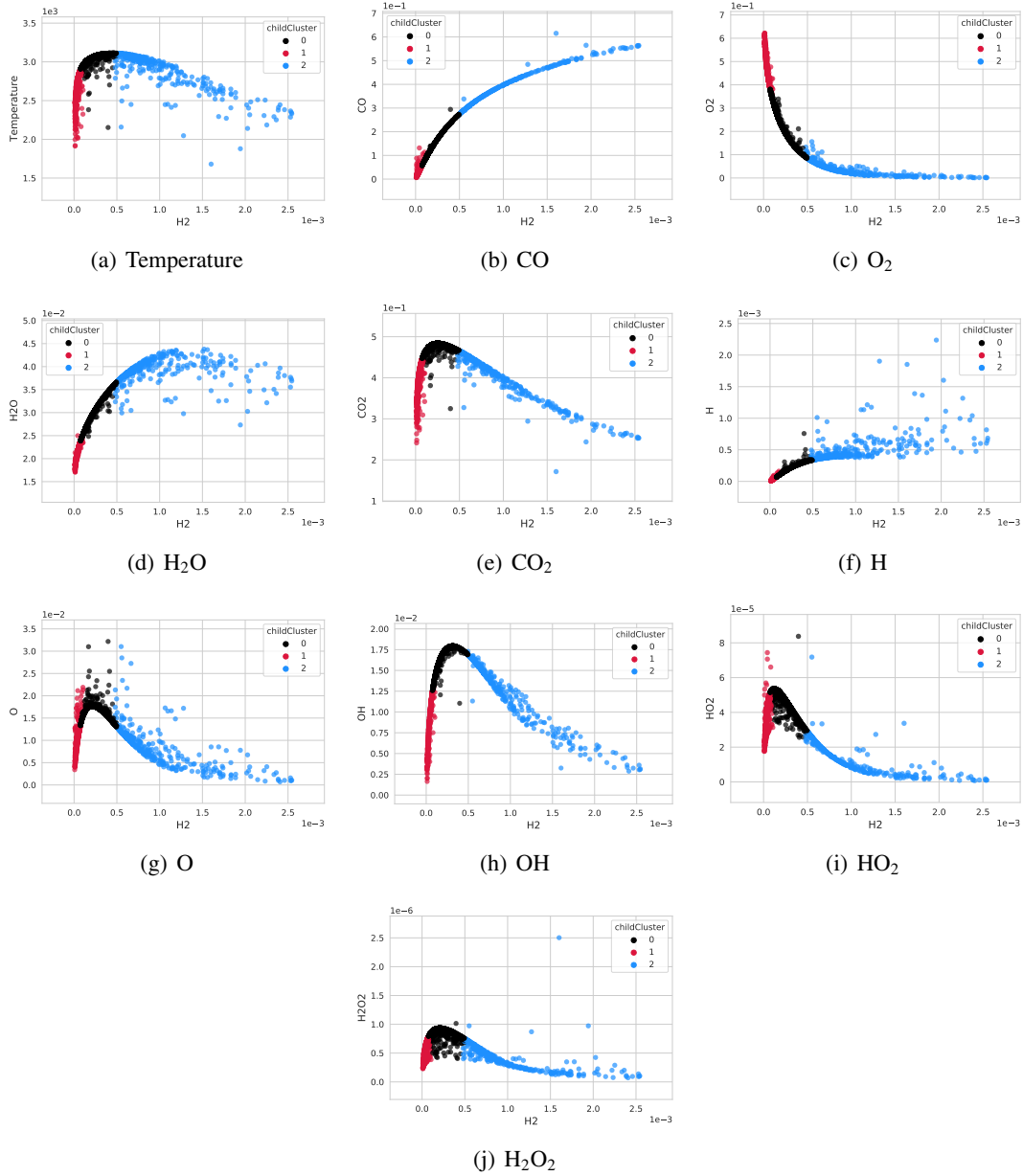


Figure 2: Data clustering for parentCluster1. Temperature [K] (a) and species mass fraction [-] (b)-(j) vs H₂ mass fraction. Red: childCluster1_0. Black: childCluster1_1. Blue: childCluster1_2.

69 this 11-species and 23 elementary reactions scheme is used to build the time evolution dataset of
 70 all stochastic particles, over 4999 time-steps of $0.3\mu\text{s}$ with a mixing time $\tau_T = 0.3\text{ms}$ (a repre-
 71 sentative value for a characteristic turbulent mixing-time as observed in shear layers for Reynolds

72 numbers typical of burners). N_2 was removed from the database for the pre-treatment and ANN
73 learning steps. The full database thus consists of the 11 feature columns (10 species and temper-
74 ature) of the 1429 stochastic particles collected over 4999 time-steps, therefore the raw data is
75 composed of $1429 \times 4999 = 7143571$ vectors of 10 components.

76 2.3. *Data pre-treatment*

77 To secure an appropriate analysis of the multivariate nature of the problem, the thermochem-
78 ical variables obtained from the solving of Eqs. 1 and 2 are going through pre-treatments, such
79 as centering and rescaling and unsupervised machine learning, like clustering with K-means [11],
80 and dimension reduction with LPCA [21], before the ANN training is to be applied. This strategy
81 is expected to close the gap between the previous works [10], in which artificial data augmenta-
82 tion was required to secure accuracy, and the introduction of complex chemistry in the numerical
83 simulation of large scale furnaces.

84 Following the recent study by D'Alessio et al. [22] in the context of adaptive chemistry for
85 reacting flow simulation, the original dataset is first pre-processed with centering and auto-scaling
86 (standardizing) to insure reliable and robust results.

87 2.3.1. *Data clustering*

88 K-means [11] is a widely used and well-established unsupervised machine learning algorithm,
89 which consists in grouping similar data into different clusters. K-means is particularly suited for
90 the classification of the micro-mixing stochastic particles, which evolve through a large variety of
91 stages from chemically-frozen flow mixing, rapid ignition, fuel oxidation and combustion up to
92 the chemical equilibrium state. Moreover, the particles from Fuel and O_2 inlets feature different
93 time histories, which benefit from being classified in separate clusters for chemistry ANN integra-
94 tion. After clustering into separate groups, every individual subset of data has similar and regular
95 distribution to ensure effectiveness of the subsequent operations.

96 The different steps in K-means used for the thermochemical quantities (species mass fractions
97 and temperature) are illustrated in Figure 1 and summarized as follows:

- 98 • Definition of the number of clusters.

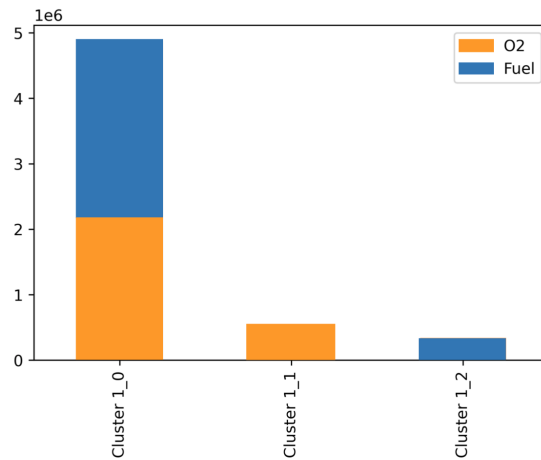


Figure 3: Repartition of data points in childCluster1_0, childCluster1_1 and childCluster1_2. Abscissa is cluster numbering, ordinate is number of data points. Orange: particles from O₂ inlet. Blue: particles from Fuel inlet.

- 99 • Selecting randomly an initial cluster centroid: To ensure the quality of clustering and im-
- 100 prove the convergence speed, the K-means++ initialization algorithm [23] is applied. The
- 101 algorithm assigns randomly a first centroid, a second centroid is then chosen as farthest
- 102 as possible to the first centroid, a third centroid is as farthest as possible to the first two
- 103 centroids, and so on.
- 104 • Assigning data point to cluster with shortest Euclidean distance.
- 105 • Updating centroid locations by averaging all data points in each cluster.
- 106 • Repeat the process until the centroid locations are converged by evaluating the shifting tol-
- 107 erance, which is chosen at $1e-20$.

108 Defining an adequate number of clusters is crucial. The usual K-means++ initialization algo-

109 rithm may lead to poor clustering in our case, where the majority of clusters concentrate in the

110 ignition and combustion stages. To overcome this difficulty, an additional hierarchical clustering

111 strategy was adopted; the first clustering leads to only 2 clusters (named parentCluster0 and parent-

112 Cluster1), which separates the low and high temperature zones. The first parent containing the data

113 of mixing, ignition and combustion stages is then clustered into 14 child clusters (childCluster0_0

114 to childCluster0_13). The subset of data in the second parent, representing the end of combustion

115 followed by the equilibrium state, requires a special treatment to guarantee the accuracy of ANN
116 training and prediction. For this reason, the second parent is classified into only 3 child clusters
117 (childCluster1_0, childCluster1_1 and childCluster1_2), and then these 3 child clusters will have,
118 respectively, 20, 10, 10 grandchildren (grandChild1_0_0 to grandChild1_0_19, grandChild1_1_0 to
119 grandChild1_1_9, grandChild1_2_0 to grandChild1_2_9). Each child cluster of the first parent and
120 each grandchild cluster of the second parent benefits from its own ANN training.

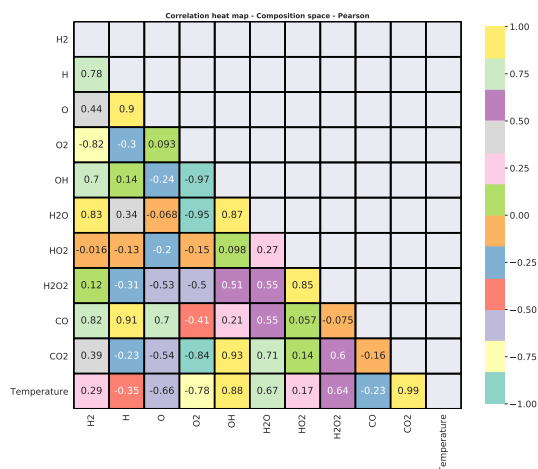
121 The effectiveness of K-means algorithm applied to the flame turbulence/chemistry interaction
122 (Eqs. 1 and 2) is illustrated in figures 2 and 3. Figure 2 shows how K-means automatically classifies
123 data in parentCluster1 (representing the end of combustion and the equilibrium state) into 3 distinct
124 subsets, i.e. childCluster1_0, childCluster1_1 and childCluster1_2. The childCluster1_1 contains
125 the particles from O₂ inlet, while the childCluster1_2 gathers the particles from Fuel inlet (Figure
126 3); both childClusters represent the end of combustion. The particles from O₂ and Fuel inlets
127 finally approach the equilibrium state and their data points are classified in a single common cluster
128 childCluster1_0.

129 2.3.2. *Local principal component analysis (LPCA)*

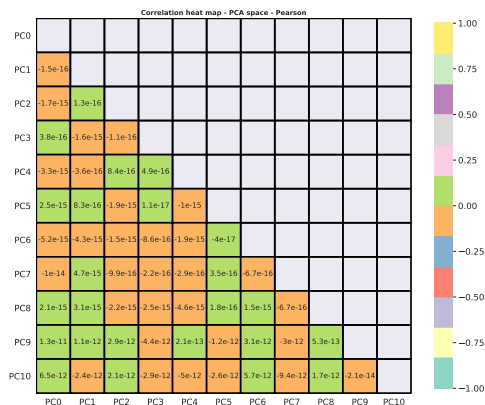
130 Principal component analysis (PCA), also known as a dimensional reduction technique, is
131 used to reduce a large number of correlated variables (species mass fractions and temperature,
132 in our case) to a smaller number of uncorrelated variables (principal components) [24]. Because
133 of the strongly non-linear character of combustion chemistry, it is usually recommended to adopt
134 a locally linear approach called ‘local PCA’ (LPCA) [21], to properly describe such dynamical
135 system.

136 In our case, each cluster represents a piece-wise variation of species mass fractions and tem-
137 perature during a specific combustion stage. The application of LPCA in each cluster transforms
138 correlated variables of high variance into the most important uncorrelated principal components
139 (PCs), which will be carefully addressed during the ANN training process. The choice of the
140 number of PCs is essential to secure a good quality of ANN prediction, and a quite high number
141 of PCs is usually required dealing with chemistry in reacting flows [22].

142 In practice, it was observed that reducing from 11 PCs to 6-8 PCs would still allow for keeping



(a) Composition space



(b) PCA space

Figure 4: Heat map showing correlation coefficients of data in grandChildCluster1.1.5. (a) Original variables in composition space. (b) PCs in PCA space.

143 more than 98% of the relevant information. However, here the full set of control variable is trans-
 144 formed into PC (i.e., 10 chemical species and temperature). Therefore, this does not reduce the
 145 size of the problem to be learned, but the parametrisation of the data from the PCs considerably
 146 eases the ANN learning process. Indeed, species and temperature are usually well-correlated, the
 147 PCA analysis transposes these variables to non-correlated PCs and the performances of ANNs
 148 then become much greater with these non-correlated inputs.

149 Two heat maps are presented in Figure 4 to show the correlation of original variables in com-

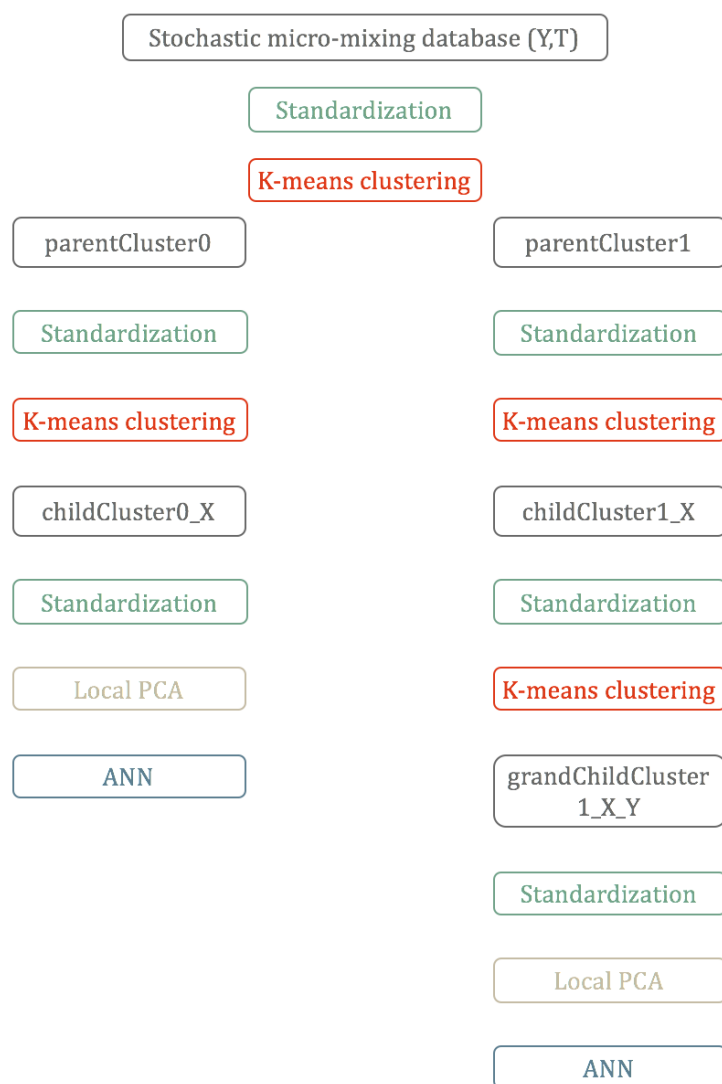


Figure 5: Chemistry reduction with trained ANN.

150 position space and of PCs in PCA space. These heat maps display the Pearson correlation coef-
 151 ficients, negative (respectively positive) value means that two variables vary in opposite (respec-
 152 tively same) directions, zero shows the absence of correlation. It is confirmed that the original
 153 variables in composition space are strongly correlated (Figure 4.a) and that PCs in PCA space are
 154 clearly uncorrelated, with practically zero correlation coefficients (Figure 4.b).

Layer	Activation function	Output shape
Input	-	(None,11)
Dense	ReLU	(None,512)
Dense	ReLU	(None,256)
Dense	ReLU	(None,128)
Dense	ReLU	(None,64)
Dense (Output)	-	(None,11)

Table 1: Structure of ANNs [10, 13]

155 *2.4. Artificial neural network*

156 The ANN regression structure (Table 1) used in this study is adopted from our previous
 157 works [10]. The ANN consists of 1 input layer, 4 dense hidden layers with the rectified linear
 158 activation function (ReLU) and 1 output layer. The total number of parameters (weights and bi-
 159 ases) is 179851.

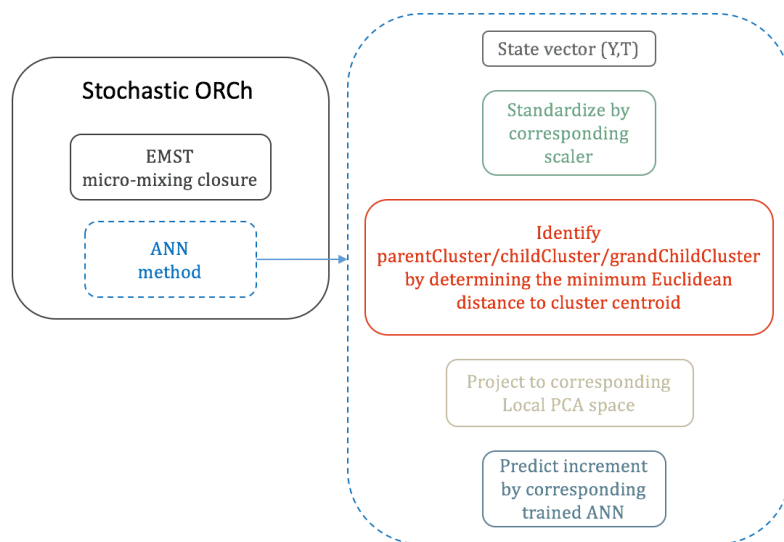


Figure 6: Flowchart of the a posteriori test. ('ORCh': Optimised and Reduced Chemistry.)

160 The ANN input is fed by the data in PCA space, composed of 11 PCs which are obtained by
 161 the projection of the 11 original variables from composition space into PCA space. The target is
 162 the increment of species composition and temperature (i.e., the ANN learns how to integrate the
 163 time evolution of chemistry). The database is split into training set (81%), validation set (9%) and

164 test set (10%) for model performance evaluation.

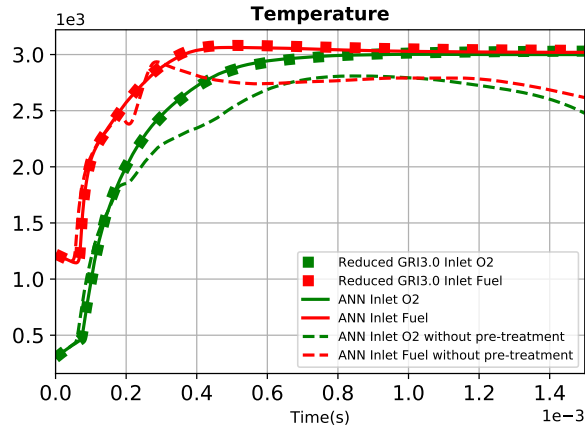


Figure 7: Time evolution of temperature [K] averaged over stochastic particles. Symbols: reference reduced scheme (Table 2 of [13]). Continuous line: Kmeans-PCA-ANN. Dashed-line: ANN without data pre-treatment. Green: O₂ inlet. Red: Fuel inlet.

165 The training process is performed using Tensorflow 2 with GPU support (NVIDIA GeForce
166 GTX 1080 Ti) and the Adam optimizer in default setting. To prevent the overfitting, the early
167 stopping callback is adopted and set as 200 epochs, which means that the training will be halted
168 after 200 epochs without improvement. Additionally, the check point callback saves the best model
169 with the lowest mean squared error (MSE) during the training process. The total training time for
170 all ANNs is about 11 hours.

171 3. Results

172 The methodology adopted in the study is summarised in Figure 5. To perform a posteriori tests
173 of the model, the evolutions of the stochastic particles are recomputed replacing the integration of
174 chemistry by the ANN, as summarised in Figure 6.

175 The time evolutions of temperature and species mass fractions averaged over the stochastic
176 particles issued from one of the inlets and computed with and without ANNs, are shown in figures
177 7-9.

178 The case without any pre-treatment of the data (dashed-line) and a single ANN rapidly deviates
179 from the reference solution (symbols). Without pre-treatment, the ANN captures the very first part

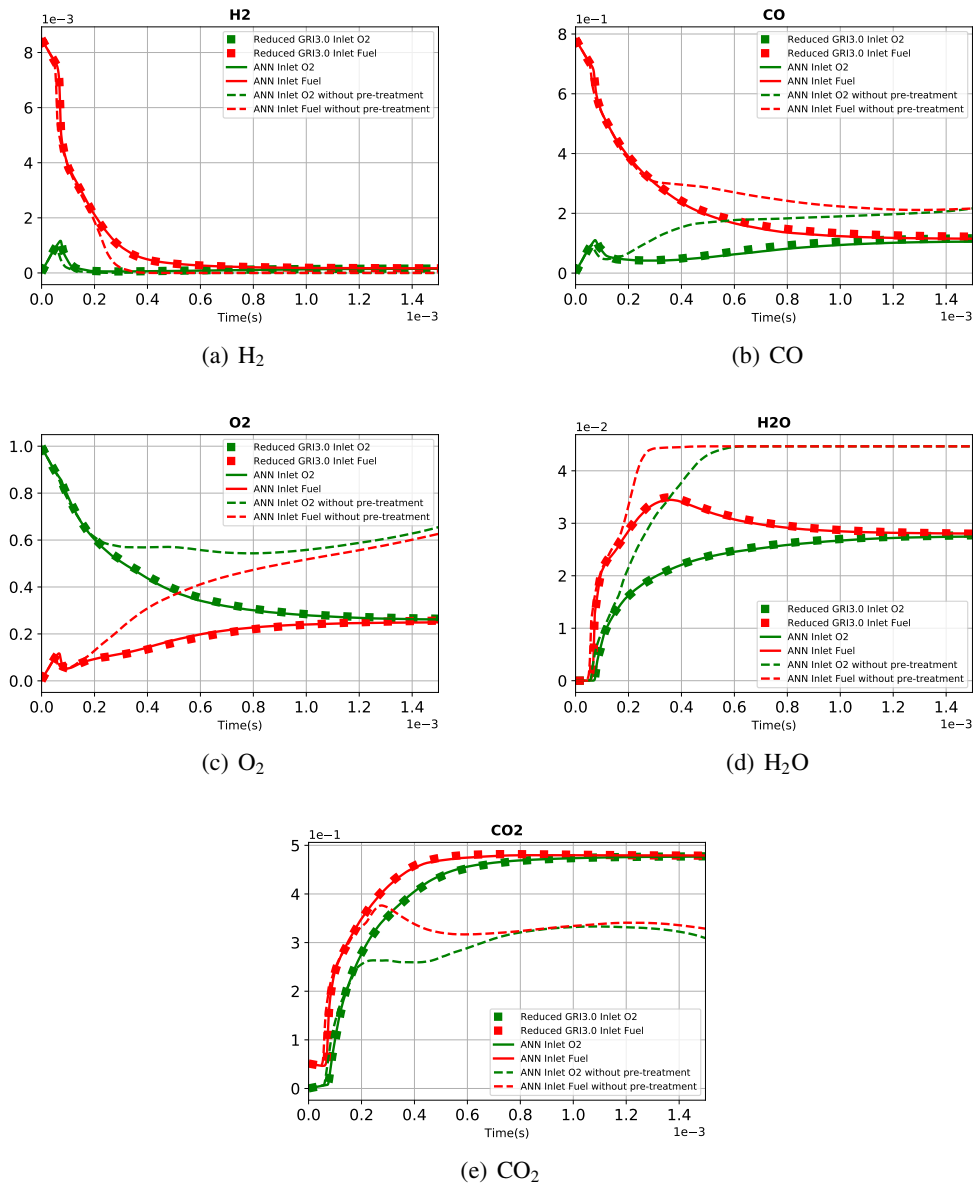


Figure 8: Time evolution of major species mass fractions averaged over stochastic particles. Symbols: Reference chemical scheme (Table 2 of [13]). Continuous line: Kmeans-PCA-ANN. Dashed-line: ANN without data pre-treatment. Green: O_2 inlet. Red: Fuel inlet.

180 of ignition, but fails to reach the equilibrium condition, see for instance the temperature response in
 181 figure 7. (Notice that one does not make use here of the introduction of manufactured intermediate
 182 solutions for H_2O_2 , as discussed in [10].)

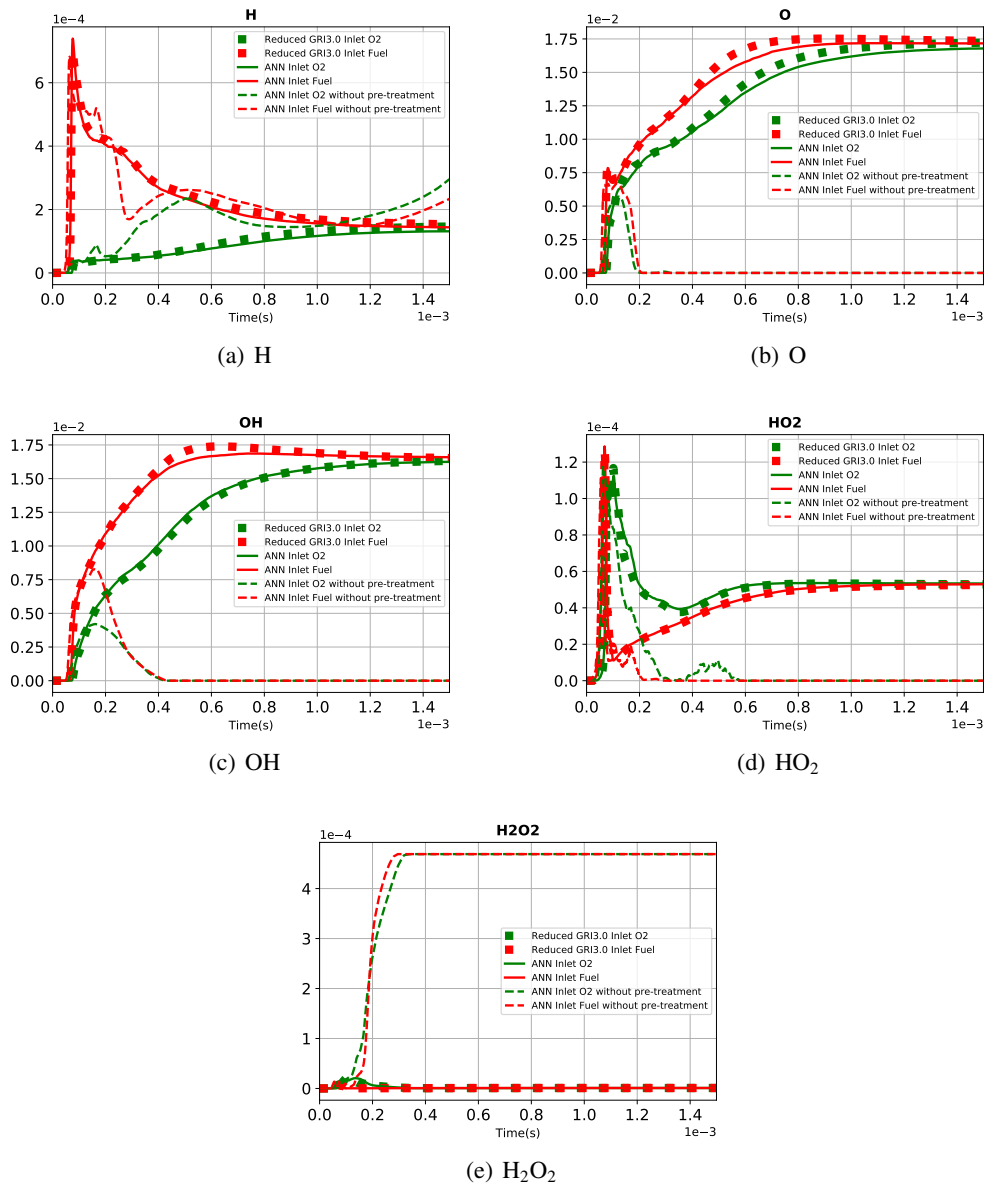


Figure 9: Time evolution of radicals and intermediate species mass fractions averaged over stochastic particles. Symbols: Reference chemical scheme (Table 2 of [13]). Continuous line: Kmeans-PCA-ANN. Dashed-line: ANN without data pre-treatment. Green: O2 inlet. Red: Fuel inlet.

183 The solution with data pre-treatment (solid lines in figures 7-9) is in good agreement with the
 184 reference solution obtained using a CPU consuming stiff-solver for chemistry (symbols). This is
 185 the case for temperature and all species considered, even radicals and intermediate ones such as O,

186 H, OH, HO₂ and H₂O₂. All the evolution stages (mixing, ignition, combustion and equilibrium)
187 are well predicted.

188 Figure 7 shows that the ignition delay of 0.08 ms is correctly predicted by the ANN model.
189 After the ignition, the temperature profiles feature a sharp increase to attain high values due to oxy-
190 combustion (the highest value is 3081K for the particles from the fuel side). Then, the temperature
191 proceed towards its equilibrium state at 3037K. The trajectories of reactants (H₂, CO, O₂), and
192 main combustion products (CO₂, H₂O) are also perfectly captured by the ANNs-based model
193 during their evolution in all specific stages, i.e. mixing, ignition, combustion and equilibrium
194 (Figure 8).

195 Regarding minor and radicals species (Figure 9), the shape and peak of the trajectories are also
196 correctly predicted except a very slight discrepancy for H₂O₂ species departing from the oxygen
197 inlet.

198 The computation time is drastically reduced by using the ANN model as given in Table 2. The
199 simulation with ANNs (single processor calculation) is 8 times faster than the simulation for the
200 reduced scheme, and 80 times faster than the simulation with the detailed GRI3.0 scheme. The
201 CPU time reduction is measured here solving for micro-mixing and chemistry (Eq. (2)). This
202 relative CPU reduction thus differs from our previous works [10], also relying on ANN for chem-
203 istry, in which the speed-up was measured solving for the aerothermochemical equations in three-
204 dimensional flows.

205 This quantification of the speed-up does not account for the preprocessing time needed to train
206 the neural networks. However, the CPU effort required for training stays much smaller than the
207 time spent performing the numerous operations required to generate a reduced chemical scheme
208 (analysis of the most important chemical species and reaction paths and optimisation of the rate
209 constants). What could slightly increase the CPU cost with ANN is the introduction of more
210 degrees of freedom which may become mandatory to reproduce very specific combustion charac-
211 teristics (cool flame effects, etc.).

Chemistry	Speed-up
GRI3.0 detailed scheme	1
Reduced scheme	10
ANNs (present work)	80

Table 2: Speed-up between chemistry descriptions.

212 4. Conclusion

213 A novel methodology based on the training of neural networks was proposed to reduce com-
 214 bustion chemistry and applied to a non-premixed syngas oxy-flame canonical configuration. The
 215 unsupervised learning technique K-means was used to cluster the entire dataset, obtained from
 216 the solution of stochastic particles in a turbulent micro-mixing system, into multiple subsets. In
 217 the case of a two-inlet problem, with one of the streams bringing the energy necessary for igni-
 218 tion, the proposed decomposition in clusters is likely to be robust and generic. Indeed, after some
 219 turbulent mixing, the mixture will always ignite to then evolve towards equilibrium. Some level
 220 of finite rate chemistry may appear, but full quenching is very unlikely, especially in the case of
 221 oxy-combustion studied here. However, the addition of heat losses and of non-adiabatic recircu-
 222 lating burnt gases may require further examination to determine the best compromise in terms of
 223 clustering, still following a similar approach.

224 Local Principal Component Analysis (LPCA) was then applied on each subset to reduce the
 225 dimension of the problem and most important principal components were retained for the ANN
 226 training process. Neural networks were finally trained with the aim to replace expensive chem-
 227 istry integration. The simulation results showed that the proposed method is able to predict the
 228 evolution of the thermochemical variables (temperature and species concentration) with excellent
 229 accuracy over the whole domain covering from mixing to ignition, combustion and finally chemi-
 230 cal equilibrium. All of those with a drastically reduced simulation time.

231 This promising result is paving the way for the introduction of reduced chemical schemes based
 232 on ANN training in reacting flow simulations, in order to mitigate CPU times without accuracy
 233 loss.

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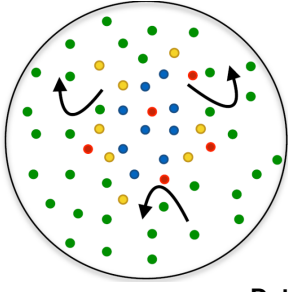
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Stochastic particles undergoing turbulence/chemistry interaction

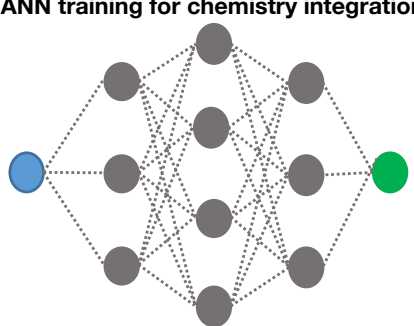


$$\frac{dY_i^p(t)}{dt} = \text{MIX}_i^p(\tau_T) + \dot{\omega}_i^p$$

$$\frac{dh_s^p(t)}{dt} = \text{MIX}_{h_s}^p(\tau_T) + \dot{\omega}_{h_s}^p$$

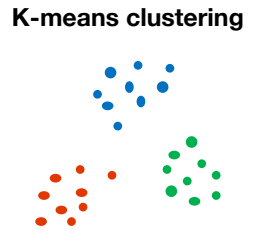
Database generation

ANN training for chemistry integration

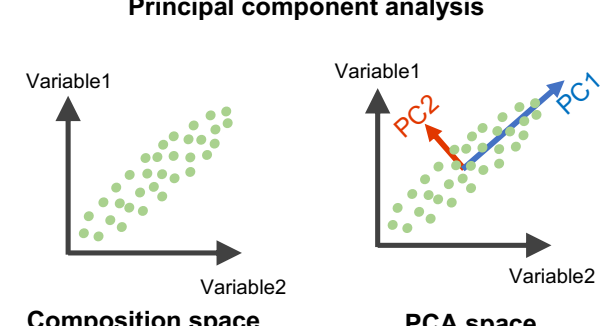


Data pretreatment for efficient machine learning chemistry integration

K-means clustering



Principal component analysis



Composition space **PCA space**

↑