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Effects of Partial Premixing and Coflow Temperature on Flame Stabilization of Lifted Jet Flames of Dimethyl Ether in a Vitiated Coflow Based on Stochastic Multiple Mapping Conditioning Approach

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Abstract: The Reynolds-averaged Navier-Stokes (RANS)-based stochastic multiple mapping conditioning (MMC) approach has been used to study partially premixed jet flames of dimethyl ether (DME) introduced into a vitiated coflowing oxidizer stream. This study investigates DME flames with varying degrees of partial premixing within a fuel jet across different coflow temperatures, delving into the underlying flame structure and stabilization mechanisms. Employing a turbulence k-ε model with a customized set of constants, the MMC technique utilizes a mixture fraction as the primary scalar, mapped to the reference variable. Solving a set of ordinary differential equations for the evolution of Lagrangian stochastic particles’ position and composition, the molecular mixing of these particles is executed using the modified Curl’s model. The lift-off height (LOH) derived from RANS-MMC simulations are juxtaposed with experimental data for different degrees of partial premixing of fuel jets and various coflow temperatures. The RANS-MMC methodology adeptly captures LOH for pure DME jets but exhibits an underestimation of flame LOH for partially premixed jet scenarios. Notably, as the degree of premixing escalates, a conspicuous underprediction in LOH becomes apparent. Conditional scatter and contour plots of OH and CH₂O unveil that the propagation of partially premixed flames emerges as the dominant mechanism at high coflow temperatures, while autoignition governs flame stabilization at lower coflow temperatures in partially premixed flames. Additionally, for pure DME flames, autoignition remains the primary flame stabilization mechanism across all coflow temperature conditions. The study underscores the importance of considering the degree of premixing in partially premixed jet flames, as it significantly impacts flame stabilization mechanisms and LOH, thereby providing crucial insights into combustion dynamics for various practical applications.

Keywords: jet in hot coflow; dimethyl ether; partially premixed combustion; multiple mapping conditioning; flame lift-off

1. Introduction
Lifted jet diffusion flames (LJDF) have practical applications in industrial burners and combustors, where the flame stabilizes away from the nozzle and thereby minimizes damage to the hardware [1,2]. The lift-off height (LOH) of these flames are highly sensitive to changes in coflow temperature. For example, a 1% change in the coflow temperature doubles the LOH for H₂/N₂ LJDF [3]. Further, at low coflow temperatures, the flame base undergoes large fluctuations, which makes the stabilization of lifted flames a complex phenomenon. Mechanisms that control flame stabilization, lift-off, and blowout have been studied extensively in the past. A comprehensive review on the stabilization of lifted
jet flames by Lyons [1] presents competing theories of premixed flame propagation, autoignition, and the role of scalar dissipation as possible stabilization mechanisms of these flames. The stabilization mechanism strongly relies on turbulent transport and chemical kinetics at the flame base [4]. A detailed analysis of the flame structure and chemical processes occurring during and prior to ignition is expected to provide insights and help us to distinguish between the premixed flame propagation and autoignition stabilization mechanisms of LJDF. For autoignition-stabilized flames, HO$_2$ and CH$_2$O radicals form during the pre-ignition phase [5]. The subsequent decomposition of these radicals leads to the production of hydroxyl (OH) radical, which triggers high-temperature reactions. In premixed flame propagation, the formation of HO$_2$ and CH$_2$O radicals remains limited to the fuel-rich region, and they are quickly consumed in the high-temperature zone [6]. Due to the mixing between fuel and oxidizer streams in lifted flames at conditions not suitable for autoignition, a partially premixed mode of combustion is often observed, leading to a two-dimensional trichorial flame (also known as triple flame) [1] consisting of a rich and a lean premixed flame and a trailing diffusion flame. The experimental setup designed by Cabra et al. [4,7] presents unique challenges for combustion models due to the delicate balance between chemical reactions and species diffusion. The detailed measurement of conditional and unconditional scalars provided by the Cabra burner series of H$_2$/N$_2$ [7] and CH$_4$/air [4] flames makes it an ideal platform for developing and validating turbulent combustion models. An analysis of H$_2$/N$_2$ jets introduced into a vitiated coflow through PDF simulations indicates that the LOH is primarily influenced by chemical kinetics rather than mixing models [3], with minimal dependence on turbulence intensity at the inlet boundary. Numerical investigations employing PDF methods demonstrate that the LOH is strongly influenced by coflow temperature and jet velocity, with the flame being predominantly kinetically controlled, thus relying on autoignition for stabilization [8]. The experimental study of Gordon et al. [9] identifies two distinct stabilization mechanisms: turbulent premixed flame propagation and autoignition, observed at low and high coflow temperatures, respectively. Subsequent numerical analyses confirm these mechanisms through transport budget comparisons [8], while Reynolds-averaged Navier–Stokes (RANS)-based conditional moment closure (CMC) simulations further support these findings [10]. Yadav et al. [11] conducted simulations of H$_2$/N$_2$ lifted jet diffusion flames using a multi-environment Eulerian PDF (MEPDF) transport approach. Despite employing an advanced turbulence–chemistry interaction model, the predictions from their study did not closely correlate with the experimental data. Various research groups have reported numerical simulations of LJDF using different methodologies. These include the LES-based CMC method [12], RANS-CMC with an extinction model [13], approximated diffusion flame presumed conditional moment [14], RANS/transported PDF [4,5], LES/presumed PDF methods [15,16] with detailed and reduced chemistries, and the LES/thickened flame method [17]. Recently, an LES-based PDF simulation [18] incorporated the effects of differential diffusion and found that molecular diffusion significantly impacts the stabilization zone of lifted H$_2$/N$_2$ flames. The presence of a wide range of length and time scales, and highly non-linear, complex interplay between turbulence and chemistry, poses a formidable challenge towards accurate numerical modeling of LJDF. Only a few models for turbulent combustion could accurately predict the flame lift-off height (LOH), especially at low coflow temperatures. Among them, presumed PDF [15], CMC [10], MMC [19,20], and transported PDF [4,5] are a few models which could capture the variation in LOH with the RANS and large eddy simulation (LES) framework. The objectives of the present work are to investigate the complex turbulence–chemistry interaction of dimethyl ether (DME) lifted flames, which have relatively complex chemical kinetics compared to methane, and to determine the effects of partial premixing of fuel jets and coflow temperature on flame characteristics, such as LOH, structure, and stabilization mechanism. Numerical simulations are performed based on an in-house RANS-MMC solver, which was validated earlier for pilot-stabilized flames of CH$_4$ [21] and DME [22] and lifted flames of H$_2$/N$_2$ [19] and CH$_4$/air [20]. Due to complex chemical kinetics and strong turbulence–chemistry
interactions, the lifted DME flame series [23] serves as an ideal candidate to evaluate the predictive capability of the RANS-MMC model. This is the first application of stochastic MMC for lifted DME flames, which display strong turbulence–chemistry interactions. In stochastic MMC, all scalars are classified into the major and the minor groups. The minor scalars, e.g., temperature and species mass fractions, are allowed to fluctuate relatively with respect to the major scalars. The mixture fraction is used as the major scalar, which is mapped with the reference space. Akin to mixture fraction-based PDF methods [10], the major scalar fluctuates with the underlying turbulent flows. The present paper is organized as follows. A brief description of the RANS-MMC approach is provided in the next section, followed by the experimental configuration and numerical details in Section 3. The numerical results from the simulations are presented in Section 4 along with an analysis of DME flames. Finally, major conclusions are drawn in Section 5.

2. Mathematical Background

In the present RANS-MMC approach, a single reference variable, \( \xi^* \), whose mapping function \( X(\xi^*) \) represents the mixture fraction \( Z \), is used. In this stochastic implementation, the reference variable, \( \xi^* \), is assumed to be Gaussian-distributed with zero mean and unit variance. A separate equation for the evolution of the reference variable, \( \xi^* \), is solved. The corresponding sets of equations for a stochastic particle method are as follows [24,25]:

\[
\text{Transport in physical space : } dx^* = U(x^*, x^*, t)dt,
\]

\[
\text{Transport in reference space : } d\xi^* = A(\xi^*, x^*, t)dt + b^*(\xi^*, x^*, t)d\omega^*,
\]

\[
\text{Transport in composition space : } dX_i^* = (W_i^* + S_i^*)dt.
\]

In the above equations, the asterisk is used to denote stochastic quantities. The positions \( x \) in physical space and the velocities \( U \) evolve according to a model represented by a Markov family. Here, the drift and diffusion coefficients are as follows:

\[
A = -\frac{\partial B}{\partial \xi} + B_\xi + \frac{1}{\rho} \nabla \cdot (\rho U^{(1)}) + \frac{2}{\rho} \frac{\partial B \tilde{P}_z}{\partial \xi},
\]

\[
2B = b^2.
\]

The chemical source terms and mixing operator are denoted by \( W_i^* \) and \( S_i^* \), respectively. The mixing operator \( S_i^* \) helps to keep \( X_i^* \) close to its conditional mean value. This ensures that mixing is local in the reference space, which is the characteristic of the MMC mixing model. Further, micromixing models are needed for the modeling of the mixing operator \( S_i^* \). The modified Curl’s [26] model was recently developed in the context of the MMC approach [19–22,27] and is utilized in the present work. In MMC-Curl, the mixing operator \( S_i^* \) involves an interaction between particles that are grouped in pairs (denoted by ’p’ and ’q’), and mixing is local in the reference space and particle pairs are mixed over a time step duration of \( \Delta t \) [28]:

\[
X_i^{*p}(t + \Delta t) = X_i^{*p}(t) + \lambda (X_i^{*p}(t) - X_i^{*p}(t)) \frac{\Delta t}{\tau_{\text{min}}},
\]

\[
X_i^{*q}(t + \Delta t) = X_i^{*q}(t) + \lambda (X_i^{*q}(t) - X_i^{*q}(t)) \frac{\Delta t}{\tau_{\text{min}}},
\]

where \( \lambda = 1 - \exp[-(w_p + w_q) \frac{N}{W}] \approx \frac{(w_p + w_q) N}{W - \frac{N}{2}} \) and \( w_p, w_q, \) and \( W \) are the weights of particles \( p \) and \( q \) and their sum, respectively. The number of particles per CFD cell is \( N \). \( \tau_{\text{min}} \) is the minor mixing time scale. The particle pair \( p \) and \( q \) is not randomly selected but selected in such a manner that \( p \) and \( q \) are local to each other in the reference space. Therefore, all particles within one CFD cell are sorted by their reference value and stored in an array. Two neighboring particles within this array are then selected for mixing. This ensures localness.
in the composition space. The mixing operator for the selected particle pairs can now be written as

\[ S^*_l = \frac{dX^{*k}}{dt} = \frac{\lambda(X^{*pq} - X^{*k})}{\tau_{\text{min}}}. \] \hspace{1cm} (8)

The minor time scale, \( \tau_{\text{min}} \), controls the conditional fluctuations of scalars around the conditional mean. The timescales \( \tau_{\text{min}} \) and \( \tau_\phi \) are related by the following relation: \( \tau_{\text{min}} = C_{\text{min}} \cdot \tau_\phi \), where \( C_{\text{min}} \) is the minor mixing time constant. Following recent nonpremixed [20] and premixed [27] RANS-MMC simulations, \( C_{\text{min}} = 0.25 \) is used here.

3. Numerical Approach

The lifted DME/air jet diffusion flames studied experimentally by Macfarlane et al. [23,29] are used in the present study. The burner has been realized with certain geometrical modifications from a similar burner used by Cabra et al. [4] for autoignition studies of hydrogen and methane lifted jet flames. The setup consists of a central fuel jet having an inner diameter of 4.45 mm. An annular coflow of hot combustion products from a lean mixture of \( \text{H}_2/\text{air} \) surrounds the central fuel jet. The coflow has an outer diameter of 197 mm with approximately 1800 holes of 1.6 mm diameter. Besides stabilizing the flames, these holes provide blockage to the flow and thereby promote turbulence. Fuel is issued from the central jet, which extends 70 mm downstream of the perforated plate. The temperature and bulk velocity of the fuel jet are 298 K and 50 m/s, respectively. Table 1 provides the conditions used in the present numerical simulations. In the experiments, the coflow temperature was varied by varying the equivalence ratio of the reactants while maintaining a constant coflow velocity of 4 m/s. Numerical simulations are performed for three different degrees of fuel/air premixing in the jet and at three different coflow temperatures.

Table 1. Inlet boundary conditions are derived from experimental data from Macfarlane et al. [23]. Here, \( Y \) represents species mass fraction.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Fuel Jet</th>
<th>Coflow</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jet composition (by volume)</td>
<td>Case 1</td>
<td>Case 2</td>
</tr>
<tr>
<td></td>
<td>Pure DME</td>
<td>Air/DME (1:1)</td>
</tr>
<tr>
<td>Temperature (K)</td>
<td>298</td>
<td>1350</td>
</tr>
<tr>
<td>Velocity (m/s)</td>
<td>50</td>
<td>4</td>
</tr>
<tr>
<td>Reynolds number (Re)</td>
<td>38,610</td>
<td>22,990</td>
</tr>
<tr>
<td>Diameter (mm)</td>
<td>4.45</td>
<td>0.36</td>
</tr>
<tr>
<td>Equivalence ratio</td>
<td>- -</td>
<td>0.0941</td>
</tr>
<tr>
<td>Stoichiometric mixture fraction, ( \xi_{\text{st}} )</td>
<td>0.06</td>
<td>0.11</td>
</tr>
<tr>
<td>( Y_{\text{O}_2} )</td>
<td>0.0</td>
<td>0.0941</td>
</tr>
<tr>
<td>( Y_{\text{N}_2} )</td>
<td>0.0</td>
<td>0.2919</td>
</tr>
<tr>
<td>( Y_{\text{H}_2\text{O}} )</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>( Y_{\text{CH}_3\text{OCH}_3} )</td>
<td>1.0</td>
<td>0.614</td>
</tr>
</tbody>
</table>

The computational domain extends to 60\( D \) and 22\( D \) in the axial and radial directions. More details about the inflow boundary conditions are provided in Table 1. At the inlet, the Dirichlet boundary conditions are used for temperature, velocity, mixture fraction, and species mass fractions, whereas the Neumann boundary conditions are employed at the outlet for all flow variables except pressure. The Neumann boundary condition is specified at all boundaries except the outlet of the domain, where the Dirichlet boundary condition is used. The underlying turbulent flow is modeled using the \( k-\varepsilon \) model with a modified set of constants \( C_{\mu} = 0.09 \), \( C_{\varepsilon_1} = 1.53 \), and \( C_{\varepsilon_2} = 1.85 \). A reduced chemical mechanism comprising 28 species and 24 chemical reactions for DME [30] derived from a full mechanism by Zhao et al. [31] is utilized. The computational domain is discretized into 120 finite-volume (FV) cells in both the axial and radial directions. At the steady state, approximately 0.6 million Lagrangian particles exist in the computational domain.
with an average of 50 particles per FV cell. Following our previous work on similar flames \cite{19,20,27}, the modified Curl’s model is used to describe the micromixing of the scalars with a major mixing time constant $C_\phi = 3$ and a minor time constant $C_{\text{min}} = 0.25$.

4. Results and Discussion

The numerical results are obtained by first running the simulations for 10 characteristic flow-through times to reach a statistically stationary condition; thereafter, statistics are collected over another 10 flow-through times. The numerical results reported herein are found to be independent of any further refinement of grid and particle resolutions. The variation in flame LOH with coflow temperatures is shown in Figure 1 for three different compositions of fuel/air mixtures in the jet. During the simulation, LOH is determined based on the first axial location where OH mass fraction ($Y_{\text{OH}}$) reaches 100 ppm at any radial location. Thereafter, both the average and the standard deviation of LOH are estimated from the time series of LOH. The standard deviation of LOH is also plotted against the average LOH in Figure 1. A comparison with available experimental measurements \cite{23} shows a decent agreement with predicted LOH. As seen in Figure 1, flames with low coflow temperature display a large fluctuation in the LOH for all three inlet compositions. In the experiments, the LOH was determined as the lowest distance of the main connected flame base from the nozzle exit, obtained using high-speed CH*-chemiluminescence images \cite{23}. For the pure DME case, as shown in Figure 1, the RANS-MMC simulations almost accurately predict the average LOH for both 1400 K and 1500 K coflow temperatures, while a slight overprediction is observed for the coflow temperature of 1350 K. The temporal evolution of LOH is shown in Figure 2. For the air/DME = 1:1 case, LOH strongly depends on the coflow temperature, as a reduction of 3.5 % in the coflow temperature (i.e., from 1400 K to 1350 K) almost doubles the LOH. Further, flames with low LOH (high coflow temperature) are found to be inherently stable, while flames with high LOH (low coflow temperature) are unstable, fluctuating, and noisy \cite{4}. For the partially premixed cases, an underprediction of LOH is observed, which continues to increase with an increase in the degree of premixing at the jet inlet. The stochastic MMC model employed herein uses the mixture fraction as the major scalar, which demonstrates a good agreement for pure DME jets (case 1). The agreement of LOH with experimental data deteriorates with an increase in the degree of premixing in the fuel jet. This may be overcome using two major scalars—one which represents the mixing of two streams and another which is the reaction progress variable. Moreover, the discrepancy in LOH prediction could also arise due to the different methodologies adopted in experiments and numerical simulations. The non-availability of excited species like CH* and OH* in the reaction mechanism does not allow us to compare LOH one-to-one with experiments. Please note that in experiments the average LOH is determined based on the chemiluminescence images predominantly from CH*. The inclusion of excited species in reaction mechanisms is possible; however, it will increase the computational cost significantly.

The temporal evolution of OH contours is shown for a air/DME = 3:1 (case 3) flame at a coflow temperature of 1400 K in Figure 3. At a low coflow temperature of 1350 K, the ignition spots form and grow in size but cannot merge with the flame base, as is evident from the OH contours shown in the last figure of this manuscript. These random spots are generated early during the start of combustion. These random spots are located within a span of 10D–30D, which causes increased fluctuations in the LOH. However, for the coflow temperature of 1400 K case, the ignition kernels form, grow, advect, and eventually mix with the flame base, suggesting that the flame stabilization is primarily due to the propagation of partially premixed flames and, to a lesser extent, to autoignition for high coflow temperature.
Figure 1. Variation in average LOH vs. coflow temperature: (left) and standard deviation plotted against average LOH (right) for case 1 (top row), case 2 (middle row), and case 3 (bottom row). Asterisk symbols represent experimental mean, and square symbols represent standard deviation from measurements [23]. Blue dashed lines represent results from RANS-MMC.

Figure 4 shows the instantaneous scatter plots for OH and CH$_2$O radicals in the mixture fraction space ($\eta$) at several axial locations for three different degrees of fuel/air premixing in the jet and at a coflow temperature of 1500 K. The scatter plots are generated after randomly identifying 10,000 unique samples from a dataset containing instantaneous data of all stochastic particles at an axial location accumulated over ten flow-through times. In Figure 4, an overlap between OH and CH$_2$O radicals is discernible up to $z/D = 7.5$ across all scenarios. Beyond this point, a clear demarcation between OH and CH$_2$O radicals emerges in the $\eta$-space at all downstream positions. Notably, the conditional peak of CH$_2$O is situated on the fuel-rich side initially, but it gradually transitions towards richer mixtures as the flow progresses downstream. An intriguing observation is the gradual reduction in the extent of overlap between OH and CH$_2$O radicals as the degree of premixing in the jet increases.
In diffusion flames, autoignition stands out as the primary stabilization mechanism. During autoignition, CH$_2$O predominantly forms within the pre-flame region. As partial premixing becomes more pronounced, the spatial separation between OH and CH$_2$O radicals becomes more pronounced as well. OH exhibits a wide distribution within the lean region, whereas CH$_2$O progressively confines itself to the exceedingly rich region, particularly evident at high coflow temperatures.

In the case of partially premixed flames under high coflow temperatures, turbulent premixed flame propagation emerges as the dominant flame stabilization mechanism. Consequently, the formation of CH$_2$O becomes somewhat restricted, as depicted in Figure 4.
by the diminishing peak value of CH$_2$O. This trend is also apparent in the contour plots. Similar findings are reported in the chemiluminescence study of the same flame.

![Figure 3](image-url)

**Figure 3.** Temporal evolution of OH contours of air/DME = 3:1 (case 3) flame at coflow temperature of 1400 K.

![Figure 4](image-url)

**Figure 4.** Instantaneous scatter plots of OH and CH$_2$O for case 1 (left), case 2 (middle), and case 3 (right) at coflow temperature of 1500 K. Stoichiometric mixture fractions and $\xi_{st}$ values for case 1, case 2, and case 3 are 0.06, 0.11, and 0.2.

The scatter plots of OH and CH$_2$O are shown in Figure 5 at $z/D = 40$ for a low coflow temperature of 1350 K. For all degrees of premixing in the jet, at a low coflow temperature, OH and CH$_2$O overlap with each other, and a broad distribution of CH$_2$O in $\eta$-space is found. The instantaneous contours of OH and CH$_2$O mass fractions are shown...
in Figures 6 and 7 for case 1 and case 3. The contours of OH and CH$_2$O for case 2 are not shown here due to brevity. The OH radical is used here as the marker to calculate the LOH. For the pure DME case, OH is mainly present in the mixing layer between the fuel jet and the hot coflow. On the other hand, CH$_2$O is produced in the fuel-rich region of the jet, while CH$_2$O concentration decreases significantly in the mixing region of jet and coflow. For partially premixed flames, at high coflow temperatures, the premixing of the fuel jet plays a dominant role in flame stabilization, while at low coflow temperatures the flame is primarily controlled by autoignition [23]. A somewhat similar phenomenon is observed from the simulations, which is evident from the contours of OH and CH$_2$O mass fractions as shown in Figure 7. At the high coflow temperature of the 1500 K case, the formation of OH kernels begins near the jet inlet. For a particular coflow temperature, the formation of OH occurs near the centerline with an increase in the degree of premixing as more O$_2$ becomes available in the fuel jet. Consequently, CH$_2$O concentration decreases near the centerline, as is evident in Figures 6 and 7. With a decrease in coflow temperature to 1350–1400 K, the formation of OH kernels occurs at farther-downstream locations. At a low coflow temperature of 1350 K, a broad distribution of CH$_2$O appears near the centerline due to initial preheating before the high-heat-release region is formed, and flame stabilization is expected to be controlled by autoignition only. In the absence of autoignition, CH$_2$O would be expected to be present adjacent to the OH layer and be consumed quickly. Thus, it may be concluded that flames at low coflow temperatures are mainly stabilized by autoignition. It is observed that for the 1350 K cases, random autoignition spots appear, as is evident from the OH contours for both pure DME and partially premixed DME/air jet cases.

Figure 5. Instantaneous scatter plots of OH and CH$_2$O for coflow temperature of 1350 K.
Figure 6. Instantaneous contours of OH (left) and CH$_2$O (right) mass fraction for pure DME jet (case 1) at different coflow temperatures: 1500 K (left), 1400 K (middle), and 1350 K (right).
5. Conclusions

The validation of lifted jet flames involving DME/air has been meticulously conducted through the application of the RANS-based stochastic MMC model. This comprehensive investigation seeks to elucidate the intricate interplay between coflow temperatures and
the degree of premixing in the fuel jet, with a particular focus on their influence on the LOH and the underlying stabilization mechanism. Within this modeling framework, a single reference variable, namely, the mixture fraction, has been judiciously employed as the fundamental parameter on which particle mixing is conditioned. To refine the description of micromixing phenomena within the stochastic MMC approach, the modified Curl's mixing model has been judiciously integrated. This model exhibits commendable efficacy in capturing the LOH for the pure DME jet, showcasing its capability to reproduce key flame characteristics. However, it is noteworthy that an observed underprediction of the LOH becomes apparent as the degree of premixing in the fuel jet increases. Moreover, the trend in the variation in LOH with coflow temperature is qualitatively captured. However, the predicted LOH values at low coflow temperatures differ from experiments. Further investigations are needed to enhance the capabilities of the modeling of partially premixed flames through additional reference variables, such as the reaction progress variable, in conjunction with the mixture fraction, to gain deeper insights into the phenomena under study. This nuanced behavior underscores the importance of considering varying degrees of fuel/air premixing when exploring the stabilization dynamics of lifted DME flames.

The numerical results gleaned from these simulations yield intriguing insights into the dominant factors governing flame stabilization under different operational conditions. Notably, the findings suggest that, at elevated coflow temperatures, the propagation of partially premixed flames assumes a paramount role in the overall stabilization process. This emphasizes the significance of understanding and characterizing the intricate balance between fuel and oxidizer streams, particularly in scenarios where the premixing of these components is prevalent.

Conversely, at lower coflow temperatures, the numerical results point towards autoigniting kernels emerging as the primary contributors to flame stabilization. This highlights the intricate interplay between autoignition processes and the prevailing environmental conditions, shaping the stabilization mechanisms in these complex combustion scenarios. Moreover, the investigation underscores that, in the context of pure DME jet flames, autoignition remains the dominant and prevailing mechanism governing flame stabilization.

In essence, this thorough examination employing the RANS-based stochastic MMC model provides a nuanced understanding of the multifaceted dynamics at play in lifted DME flames. As a pioneering application of this model to such flames, this study contributes valuable insights into the complex interplay between turbulent combustion, premixing, and autoignition, offering a stepping stone for further advancements in the understanding and modeling of intricate combustion processes in practical applications.


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