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NUMERICAL SIMULATION AND UNCERTAINTY QUANTIFICATION OF A GENERIC DROPLET EVAPORATION VALIDATION TEST CASE

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1 *Alternative jet fuels have a high potential to reduce emissions in aviation. A big difficulty for their introduction is the costly and lengthy assessment of fuel effects on combustion performance. In the present work, the evaporation of free-falling droplets of realistic size ($D \approx 80 \mu\text{m}$) in a well-defined vertical laminar heated flow is studied experimentally and numerically. Measurements of droplet diameters and velocities using microscopic double-pulse shadowgraphy are conducted for several single species and systematically chosen conventional and alternative multi-component jet fuels. The results show that the experiment is fuel-sensitive with respect to evaporation. In this study, special attention is paid to unknown or uncertain boundary and initial conditions, which serve as input in the validation of the numerical models. Therefore, non-intrusive non-deterministic simulations using Polynomial Chaos Expansion are performed to account for these uncertainties. The uncertainty quantification displays that overall uncertainties are small enough to distinguish between the different fuels and to predict fuel-dependent effects on evaporation. Nevertheless, the uncertainties are not negligible. A sensitivity analysis shows a high sensitivity of the evaporation to the offset of the droplet from the centerline and to the uncertainty of the inflow gas temperature. Reducing the uncertainties of the two above-mentioned conditions is most promising in enhancing the validation experiment.*

KEY WORDS: *Uncertainty quantification, Sensitivity analysis, Alternative jet fuels, Multi-component evaporation modeling, Fuel sensitivity*

1 1. INTRODUCTION

2 In order to reduce CO₂ emissions of the aviation sector, an increasing percentage of alternative, synthetic components
3 are added to conventional fossil jet fuels (Blakey et al., 2011; Kaltschmitt and Neuling, 2017). Safety regulations
4 therefore require a thorough screening and analysis of these added components and their effect on the engine perfor-
5 mance, as done in the research programmes JETSCREEN (2020) and NJFCP (Colket et al., 2017).

6 Besides chemical properties influencing the chemical reactions, the physical properties that govern atomization and
7 evaporation play an important role for the combustor operability. Recent findings show that preferential vaporization
8 impacts the lean blow-out (LBO) limits (Won et al., 2019) and the emissions (Eckel et al., 2019) of jet-fuel combus-
9 tors.

10 Due to the crucial role of evaporation in spray combustion, the development of models for multi-component evap-
11 oration is an active research topic. The models can be divided into continuous thermodynamic models (Cooney
12 and Singer, 2019; Hallett, 2000; Le Clercq et al., 2009), distillation curve methods (Burger et al., 2003), discrete-
13 component methods (Ebrahimian and Habchi, 2011; Govindaraju and Ihme, 2016; Lupo and Duwig, 2018; Ra and
14 Reitz, 2009; Tonini and Cossali, 2019) and quasi-discrete models (Sazhin et al., 2011). However, the multi-component
15 evaporation models oftentimes lack a proper validation. This is on the one hand because of unknown fuel compo-
16 sitions in the experiments (Brandt et al., 1998; Sanjosé et al., 2008) or intrusive measurement setups, e.g. using
17 suspension fibers (Chauveau et al., 2008). On the other hand, the experimental data are often limited to single species
18 (Deprédurand et al., 2010; Gounder et al., 2012; Verdier et al., 2017) or a small number of fuel components (Birouk
19 and Gökalp, 2002; Daif et al., 1998; Maqua et al., 2008; Rauch et al., 2012; Stengele et al., 1999) as well as to bound-
20 ary conditions, which are far from realistic engine-conditions (Brenn et al., 2007; Wilms, 2005). Unquestionably,
21 all these validation data sets provide valuable information but they do not cover the entire range of application of
22 multi-component evaporation models.

23 Furthermore, model validation is usually carried out after the validation experiment was designed and data are
24 published. This can lead to situations in which results are very sensitive to certain boundary conditions, which were
25 either not measured at all or not determined with the needed accuracy. The unknown parameters need to be calibrated
26 and in consequence the validation is weak. Although the models used in the simulations must be validated before
27 being used for prediction (Oberkampf and Roy, 2010), they can play a major role in reducing design iterations and
28 improving existing experiments. In this context, a close collaboration and combination of numerical simulation and
29 experiment is desirable. Propagating uncertainties stemming from the experiment through the numerical simulation
30 can help to estimate the effect on the quantities of interest. Consequently, sensitivity studies can be used to identify

1 the most influential input uncertainties that can then be reduced by optimizing the experiment. Despite the potential
2 benefits of uncertainty analysis in combustion simulations, there are only a few studies found in the literature, e.g. for
3 chemical kinetics (Prager et al., 2013), fuel evaporation (Errante et al., 2018; Lupo and Duwig, 2020; Rauch et al.,
4 2016; Shashank et al., 2011), spray boundary conditions (Van Dam and Rutland, 2016) and spray combustion (En-
5 derle et al., 2020).

6 Yet, to the authors' knowledge, there is no study available aiming at using the synergy of experiments and non-
7 deterministic numerical simulations to improve both the experiment and the modeling. Therefore, the current study
8 aims to provide accurate validation data for evaporation of single droplets alongside non-deterministic simulations
9 propagating input uncertainties that arise from unknown boundary conditions. In contrast to deterministic approaches,
10 a non-deterministic approach eliminates the need to calibrate the uncertain boundary conditions and provides a quan-
11 titative measure on the often larger-than-expected uncertainties. Analysis of the propagated uncertainties and sensi-
12 tivities allow a methodological improvement of the experimental setup and thus minimize the uncertainties.

13 The paper is structured as follows. An experiment where droplets of realistic size ($D \approx 80 \mu\text{m}$) are injected in a
14 laminar pre-heated flow is presented in section 2. Next, a summary of the numerical modeling (section 3) and the
15 investigated four single-component and four multi-component fuels (section 4) is given. Measurement results of
16 droplet diameters over time are provided in section 5. Thereafter, the methods used for uncertainty quantification
17 are described (section 6), followed by the results of the non-intrusive non-deterministic simulations of the droplet's
18 evaporation behavior (section 7). Finally, the findings are discussed and conclusions are drawn in section 8.

19 2. EXPERIMENTAL SETUP

20 The fuel droplet evaporation is measured in a vertical channel sketched in Fig. 1(a). An air flow of 30 g/min is
21 electrically heated to $T \approx 250 \text{ }^\circ\text{C}$, passes through a porous bronze matrix and then flows downwards with an average
22 velocity of about 0.2 m/s in a channel of $60 \times 60 \text{ mm}^2$ cross-section. Optical access for shadowgraphy is provided
23 by utilizing quartz glass for the channel side walls. A piezo-driven dispenser head (Microdrop MD-K-140) is located
24 above the bronze matrix and injects single droplets of $D \approx 80 \mu\text{m}$ into a vertical steel tube whose exit is located
25 5 mm below the matrix. The droplets are generated periodically with a frequency of 40 Hz, which ensures that the
26 distance between droplets is larger than 200 diameters and thus prevents inter-droplet interaction. An air flow of
27 0.5 g/min and $T \approx 30 \text{ }^\circ\text{C}$ is generated in the vertical tube below the droplet generator resulting in a fully developed
28 laminar flow with an average velocity of about 1 m/s. The flow conditions equate to a Reynolds number of $\text{Re} \approx 300$
29 and an average droplet Reynolds number of $\text{Re}_d \approx 0.3$. Therefore, well-defined boundary conditions in terms of

1 velocity and temperature are available for the droplet evaporation domain. The evolution of droplet diameter and
2 velocity is measured using microscopic double-pulse shadowgraphy. The laser pulses from a dual-cavity Nd:YAG-
3 Laser ($\lambda = 532 \text{ nm}$, $E = 2 \times 80 \text{ mJ}$, $50 \leq \Delta t \leq 200 \mu\text{s}$) are widened by a concave lens and then directed onto a
4 fluorescent screen of $d = 100 \text{ mm}$, which provides the required non-coherent illumination. Resulting double-images
5 of the droplet shadow are recorded using a long-distance microscope (Questar QM100) mounted on a CCD camera
6 (1.4 MP). The droplet size $D(z)$ and axial velocity $v(z)$ are calculated from the image pairs by an in-house image
7 processing code. For the variation of z , the channel is moved vertically using a translation stage while the optical
8 setup remains fixed. Thereby, measurements of $D(z)$ and $v(z)$ are made every $\Delta z = 5 \text{ mm}$ starting from $z_0 = 1 \text{ mm}$
9 until the droplet is fully vaporized. The corresponding times $t(z)$ are calculated using the measured velocities as
10 $t(z) = \int_{z_0}^z 1/v \, dz$.

11 It is noteworthy that the experiment can also be operated with a matrix burner instead of the electrical heater, which
12 enables investigation of droplet evaporation at temperatures up to 1200 K, as demonstrated in a recent study (Stöhr
13 et al., 2020).

14 3. NUMERICAL MODELING

15 3.1 Gas flow solver

16 Simulations are carried out using the DLR in-house CFD code THETA (Di Domenico et al., 2011), which employs
17 a 3D finite-volume solver for unstructured grids. The underlying equations are the conservation of mass, momentum,
18 species and enthalpy. Due to the low flow velocities, buoyancy effects are included in the convection-diffusion equa-
19 tions for heat and species. The convective and diffusive fluxes are discretized using second-order upwind and central
20 schemes, respectively. The Navier-Stokes equations are solved using the Semi-implicit Method for Pressure Linked
21 Equations (SIMPLE).

22 The computational domain is displayed in Fig. 1(b). It consists of a cylinder at the top and a cuboid representing the
23 droplet tube and the channel, respectively. The fully unstructured grid possesses a strong clustering near the walls and
24 close to the liquid injection system to resolve boundary effects and the droplet evaporation.

25 3.2 Dispersed phase solver

26 For the simulation of the liquid phase, THETA is coupled to the DLR in-house solver SPRAYSIM (Eckel et al., 2016),
27 which uses a Lagrangian particle tracking framework. Due to the low frequency of the droplet generator, the mass

1 and momentum source terms in the gas field equations are negligible. As a consequence, only a one-way coupling is
2 established.

3 The liquid consists of a multi-component mixture based on the chemical analysis of the individual jet fuels by means
4 of a comprehensive 2D gas chromatography coupled with a mass spectrometry (GCxGC-MS) system. Differences
5 in volatility of the individual species are modeled by two types of multi-component evaporation models. For fuels
6 with a few components, i.e. the four single-component fuels (iso-octane, n-decane- n-dodecane, 1-hexanol) and the
7 B1 fuel (Alcohol-to-Jet), a discrete-component method (DCM) is used. For complex fuels with a large number of
8 components, i.e. A1, C1, and C5 fuels, the continuous thermodynamics model (CTM) of Le Clercq et al. (2009) and
9 Doué et al. (2006) is applied. It assumes that the species distribution can be approximated by a continuous description
10 via probability density functions (Hallett, 2000). The fuel components are grouped into fuel families (n-alkanes,
11 iso-alkanes, cyclo-alkanes, mono-aromatics, di-aromatics), as shown exemplarily in Fig. 2. In the paper at hand, the
12 probability density function (PDF) of each family follows a Γ -distribution. This reduces the number of degrees of
13 freedom in the evaporation model by orders of magnitude, which cuts down the computational costs. The underlying
14 evaporation model for DCM and CTM is the model of Abramzon and Sirignano (1989) with slightly modified terms
15 for Reynolds-dependence (Eckel et al., 2018). It assumes rapid mixing within the droplet.

16 The Biot number is in the order of $Bi \approx 0.11$ and thus only slightly above the limit for a “thermally thin” medium
17 ($Bi = 0.1$), justifying the rapid mixing model’s assumption of a uniform temperature inside the droplet. With respect
18 to species diffusion in multi-component droplets, the Lewis number shows values in the order of $Le \approx 37$. Thus,
19 species diffusion is clearly slower than the heat diffusion. However, internal convection can significantly increase
20 the species mass transfer inside the droplet. In this regard, Wilms (2005), who used rainbow refractometry in a setup
21 similar to this study, observed no species gradients inside the droplets during evaporation. He assumed that the droplet
22 generator induced an internal circulation of the liquid, which persists during the evaporation process. The existence
23 of inner circulations supports the assumption of rapid mixing.

24 **3.3 Boundary conditions**

25 The heated matrix is modeled as a source of hot gas with a pre-defined constant mass flow rate and temperature. The
26 lateral boundaries are represented by isothermal walls. A fixed pressure is applied at the outlet. The experimental
27 setup does not allow a direct measurement of the initial droplet diameter and droplet velocities because the droplet
28 generator is located inside a tube without optical access (Fig. 1 (a)). Therefore, the droplet initial conditions are taken
29 from the manufacturer’s specifications listed in Table 2. As previously mentioned, the droplet composition matches

1 the different fuel compositions determined by chemical analysis (see section 4).

2 4. FUELS

3 For the present study two sets of fuels were selected that provide a broad variation of physical properties in order to
4 analyze their effects on the evaporation characteristics. The first group consists of four single-component fuels (iso-
5 octane, n-decane, n-dodecane, 1-hexanol) with different boiling points (Fig. 3). They are used to analyze the quality
6 of the DCM evaporation model. The second group consists of four multi-component fuels that represent a wide
7 range of possible conventional and alternative jet-fuels. They were selected by the JETSCREEN research programme
8 (JETSCREEN, 2020) and are used to explore the limits of the CTM evaporation model in this study. The composition
9 of the multi-component fuels is listed in Table 1.

10 5. EXPERIMENTAL RESULTS

11 First, the experimental results of the droplet evaporation for the single component fuels are discussed by means of
12 Fig. 4. The experiments reveals the volatility differences between the fuels. After a short initial heat-up phase, the
13 droplets behave according to the D^2 -law, evaporating at constant temperature (Law, 1982). While the three alkanes
14 follow the trend of their respective boiling temperatures T_b , 1-hexanol evaporates slower than n-dodecane despite its
15 lower T_b . This is explained by the higher heat of vaporization of 1-hexanol ($H_v = 603 \text{ J/g}$) in comparison to the
16 one of n-dodecane ($H_v = 361 \text{ J/g}$) (Kim et al., 2019). A more detailed discussion of the (temperature-dependent)
17 influence of latent heat on evaporation rate is provided in our recent study (Stöhr et al., 2020).

18 Second, Fig. 5 displays the droplet evaporation for the multi-component fuels. After the initial phase of heating and
19 thermal expansion, the evaporation of the lighter fuel components starts. Especially for the B1 fuel the differences
20 between the lighter, fast evaporating and the heavier, slow evaporating components are apparent. The reason for this
21 is that B1 mainly contains two components, iso-dodecane (highly-branched $C_{12}H_{26}$) and iso-cetane (highly-branched
22 $C_{16}H_{34}$). The order of the evaporation of the remaining fuels is in agreement with the distillation curves, where A1
23 evaporates first, followed by C5 and C1. The differences between the multi-component fuels are measured with high
24 precision.

25 6. NON-DETERMINISTIC (PROBABILISTIC) APPROACH FOR UNCERTAINTY QUANTIFICATION

26 Sources of uncertainty can be partitioned into three categories: numerical, model form and input uncertainties (Ober-
27 kampf and Roy, 2010). The present study focuses on the impact of input uncertainties on a quantity of interest Q .

1 Input uncertainties include parameters used in the simulation model and boundary conditions. The input uncertainties
 2 are propagated through the simulation model \mathcal{M} by a non-intrusive method, where \mathcal{M} is considered as a black-box
 3 and the probabilistic behavior is achieved from a finite number of random samples of \mathcal{M} (Roy and Oberkampf, 2011).

4 **6.1 Uncertainty propagation**

5 The most clear-cut sampling technique is the Monte Carlo method (Fishman, 2013). However, this technique requires
 6 a large number of samples to return reliable statistics, making it unsuitable for large scale simulation problems.
 7 Therefore, it is replaced by a surrogate model using Polynomial Chaos Expansion (PCE) (Le Maître and Knio, 2010;
 8 Xiu and Karniadakis, 2003) on a sparse grid (Smolyak, 1963). A typical PCE of the quantity Q , driven by n inputs
 9 $\vec{\xi} = (\xi_1, \dots, \xi_n)$ is given as

$$Q = f(\xi) \approx \sum_{k=0}^P \alpha_k \Psi_k(\vec{\xi}) = \mathcal{M}_{PCE}, \quad (1)$$

10 where α_k are the modes and Ψ_k are multivariate polynomials of $\vec{\xi}$. The approximation of the typically infinite series
 11 depends on the total degree p of the multivariate polynomials Ψ_k leading to $P + 1 = (n + p)! / (n! p!)$, where P is the
 12 truncation order of the series. For a given PCE the mean \mathbb{E} and variance \mathbb{V} are directly calculated as

$$\mathbb{E} = \alpha_0 \quad \text{and} \quad \mathbb{V} = \sum_{k=0}^P \alpha_k^2 \langle \Psi_k^2 \rangle. \quad (2)$$

13 **6.2 Sensitivity analysis**

14 Subsequent to the uncertainty quantification with PCE, the resulting model approximation \mathcal{M}_{PCE} is used to directly
 15 calculate the sensitivities of the quantity of interest Q to the inputs $\vec{\xi}$. The sensitivities are computed by variance-
 16 based decomposition of the entire variance \mathbb{V} of the model output $\mathcal{M}(\vec{\xi})$ into contributions of the different inputs
 17 $\mathbb{V}[\mathcal{M}(\vec{\xi})|\xi_i]$ (Sobol, 1993; Sudret, 2008). The so-called Sobol indices

$$S_i = \frac{\mathbb{V} \left[\mathbb{E} \left[\mathcal{M}(\vec{\xi}) | \xi_i \right] \right]}{\mathbb{V} \left[\mathcal{M}(\vec{\xi}) \right]} \quad \text{and} \quad S_i^T = \frac{\mathbb{V} \left[\mathbb{E} \left[\mathcal{M}(\vec{\xi}) | \xi_{\sim i} \right] \right]}{\mathbb{V} \left[\mathcal{M}(\vec{\xi}) \right]} \quad (3)$$

18 represent the main effect and the total effect indices, respectively. The main effect indices S_i correspond to the direct
 19 contributions of ξ_i to the variance of \mathcal{M} , whereas S_i^T also include interactions with other variables.

1 **6.3 Definition of the UQ problem**

2 The aforementioned methods are applied to the numerical simulation of the evaporation test case. Sandia DAKOTA
3 6.10 (Adams et al., 2009) is used to construct and evaluate the UQ methods, with the THETA-SPRAYSIM framework
4 as a black-box.

5 In classical, deterministic, numerical simulations the unknown boundary conditions are estimated or calibrated to
6 yield a best estimate for the known data. Furthermore, the uncertainties of the known boundary conditions could
7 be used to tweak the simulation to fit the experimental data. Therefore, the validation of the model is weak. In this
8 study, the unknown boundary conditions of the gas field are estimated, however the uncertainties introduced by the
9 calibration will be considered in the non-deterministic study.

10 *6.3.1 Definition of boundary conditions*

11 As a first step, before conducting the non-deterministic simulations, the boundary conditions of the gas field and
12 droplet initial conditions are classified by the type of method used to determine their values (Table 2). Except for the
13 wall temperatures of the test case, all other boundary and initial conditions are known. The values and uncertainties
14 of the wall temperatures are estimated as follows. The only information available to determine the wall temperatures
15 are the measurements of the centerline temperature by thermocouples. The wall temperatures are estimated using
16 DAKOTA to meet the measured centerline gas temperatures $T_g(z)$. For this purpose, wall temperatures at three dif-
17 ferent positions ($z = 0, 100, 200\text{mm}$), interpolated by Akima splines (Akima, 1970) were optimized with an adaptive
18 nonlinear least-squares algorithm (NL2SOL, Dennis Jr et al. (1981)) already implemented in DAKOTA. In contrast to
19 deterministic simulations, the estimation of the wall temperatures in this manner reduces the uncertainties stemming
20 from the unknown boundary conditions rather than disregard them. The best parameters for the wall temperatures
21 yield the results in Fig. 6 and reflect the evolution of the measured centerline temperature. The parameters are listed
22 in the value column of Table 2. In particular, the temperature drop due to buoyancy effects at $z \approx 175\text{ mm}$ is met
23 correctly. In this respect, it is noteworthy that the temperature drop does not influence the evaporation behavior, since
24 all fuels completely evaporate before. The authors would like to emphasize that only the wall temperatures are deter-
25 mined by a calibration while none of the models used in the gas flow or dispersed flow solver are specifically tuned
26 to the test case.

1 6.3.2 Quantities of Interest

2 As a second step, the quantities of interest Q have to be defined. For the uncertainty propagation, the evolution of
3 the normalized squared diameter D^2/D_0^2 over time is chosen as Q . As the examination of each point in time of the
4 temporal diameter evolution would be too extensive for the subsequent sensitivity analysis, three global metrics for
5 the evaporation are chosen. The evaporation rate K , the total evaporation time t_t and the unsteady heat-up time

$$t_{us} = t_t - 1/K \quad (4)$$

6 are illustrated in Fig. 7. The unsteady heat-up time t_{us} is the time at which $D = D_0$. It is extrapolated back from the
7 total evaporation time t_t using a linear evaporation rate K . Despite the dependency of t_{us} on the other two quantities
8 of interest, it is added to get a better picture of the whole evaporation process.

9 6.3.3 Characterization of input uncertainties

10 The third step of the definition of the UQ problem contains the characterization of the input uncertainties. For the
11 sake of clarity, the input uncertainties are divided into two groups, i.e. uncertainties in the flow boundary conditions
12 and uncertainties in the droplet initial conditions. All input quantities are treated as epistemic interval-valued uncer-
13 tainties, defined by the respective minimum and maximum as summarized in Table 2.

14 Although the flow boundary conditions have been estimated to meet the measured centerline temperature, they are not
15 free of errors. The thermocouple measurements are subject to measurement errors and are very sensitive to the radial
16 position of the thermocouple. Especially for regions near the tube exit, small deviations in the radius lead to big shifts
17 in the measured temperature. Therefore, an uncertainty of ± 15 K was estimated for the channel wall temperatures T_z
18 at $z = 0, 100$ and 200 mm, with the ambient air temperature as the lower limit. For the wall temperature of the tube
19 T_t as well as the temperature of the heated air inflow T_{in} , the uncertainties are considered to be ± 5 K.

20 The droplet initial conditions are based on the manufacturer's specifications for the droplet initial diameter D_d and
21 the initial velocity v_d . The uncertainties for the droplet initial conditions are estimated from previous measurements.
22 The droplet temperature T_d is expected to be around the ambient air temperature measured by a thermocouple. Addi-
23 tionally, the uncertainty in the starting position needs to be considered in the UQ study. As can be seen from Fig. 8
24 showing the droplets' offset r from the centerline, the different single component droplets have slightly different
25 trajectories. This leads to different gas velocities and temperatures seen by the droplet. The uncertainty in the radial
26 position is assumed to be 1.8 mm, which is the maximum offset for n-dodecane at the tube exit ($z = 1$ mm).

1 7. RESULTS OF NON-DETERMINISTIC SIMULATIONS

2 The PCE surrogate model \mathcal{M}_{PCE} is built by calculating 199 samples defined by the Smolyak quadrature for the $n = 9$
3 inputs. Hermite orthogonal basis polynomials are used as multivariate polynomials Ψ_k . The accuracy of the surrogate
4 model \mathcal{M}_{PCE} is examined through holdout validation against 20 additional holdout datasets. The normalized root
5 mean squared error is below 1 % at all vertical positions.

6 7.1 Results of uncertainty propagation

7 Initially, the normalized squared diameter evolutions of the single component fuels are compared to the measure-
8 ment results. Fig. 9 illustrates that the mean \mathbb{E} of the simulations predicts the measured evaporation behavior for all
9 single components. Assessing the uncertainties, the results can be divided into two sections. In the early stages of
10 evaporation, the uncertainties are too large to distinguish between the different fuels. Later, when the droplets behave
11 according to the D^2 -law, the difference in evaporation between the three alkanes can be distinguished, i.e. the pre-
12 dicted intervals do not overlap. Not only is the calculated mean in close agreement with the experimental data, but the
13 predicted uncertainties also fully enclose all measurements. Thus, no error is identifiable and the evaporation model
14 is proven to be accurate for the single component fuels. It is also noteworthy that an earlier onset of evaporation inside
15 the tube and a faster evaporation cause the larger uncertainties for iso-octane.

16 The four multi-component fuels are shown in Fig. 10. For the initial phase ($t/D^2 < 5 \text{ s/mm}^2$), the mean of the
17 simulations match the experimental data for all four fuels. The trend between all four fuels is also predicted correctly.
18 Even though the predicted intervals overlap in the early stages of evaporation, the different fuels can be distinguished
19 in the later stages. Moreover, the fuels A1 and B1 lie within the predicted intervals for the major part of the evapo-
20 ration process. The deviation of the B1 fuel for later stages of evaporation can be attributed to impurities in the fuel.
21 If the impurity is caused by a heavier fuel component, even an amount 1 vol% corresponds to a remaining diameter
22 of $D = 17.2 \mu\text{m}$ or $D/D_0 = 0.046$, matching the measured values for the later stages of the evaporation. The close
23 agreement of the B1 fuel with the experiments also confirms the assumption of rapid mixing inside the droplet. In
24 contrast to the A1 and B1 fuel, the predicted intervals for C1 and C5 do not cover the measurement data in the later
25 stages of the evaporation.

26 The discrepancy between the simulation and measurement of the C1 and C5 fuel cannot be accredited to the input
27 uncertainties, which were taken into account in the non-deterministic simulation. As previously shown, the evapo-
28 ration model is accurate for single-component fuels. Furthermore, the errors associated with use of Γ -functions that
29 don't precisely match the measured compositions were found to be small in a previous study (Ruoff et al., 2019).

1 Therefore, the deviation has to originate from the CTM evaporation model or the underlying property model. A first
2 analysis suggests that the physical properties predicted by the CTM, e.g. heat capacity (c_p) and heat of vaporization
3 (H_v), of the C-fuels need to be improved. This is presumably related to the high content of di-aromatics in these fuels.
4 A detailed analysis of the CTM property correlations is necessary, which lies outside the scope of this study and will
5 be subject of future work.

6 **7.2 Results of sensitivity analysis**

7 To evaluate the contribution of the uncertain input parameters to the variances in the simulation results, the Sobol
8 indices introduced in Equation 3 are calculated for the A1 reference fuel. The A1 reference fuel is chosen since the
9 prediction for the A1 fuel showed the closest agreement with experimental results. The bars in Fig. 11 illustrate the
10 direct contribution of each input parameter to the variance in each quantity of interest. The total Sobol indices S_i^T and
11 main Sobol indices S_i are nearly identical, indicating very small interactions between the inputs, and are therefore
12 not shown in Fig. 11.

13 For the evaporation rate K , the inlet temperature of the heated air inflow is identified as the dominant parameter,
14 followed by the radial offset r_d and the tube wall temperature T_l . All of the three parameters influence the ambient
15 temperature, which the droplet experiences along the trajectory. Consequently, the evaporation rate changes.

16 Likewise, the total evaporation time t_t also depends on parameters influencing the ambient temperature. However,
17 the offset r_d from the centerline has a larger influence. As the gas velocity decreases towards the tube walls due to
18 boundary layer effects, droplets experience longer residence times in the hot regions. Furthermore, the droplet initial
19 diameter D_d contributes directly to t_t since more mass needs to evaporate.

20 For the unsteady heat-up time t_{us} , the Sobol indices shift towards the droplet initial conditions. Similarly to the
21 total evaporation time, the deviation from the centerline r_d influences the residence time and thus the droplet heat up
22 before entering the channel. Furthermore, a larger initial diameter D_d increases the droplet mass so that more energy
23 is needed to heat up the droplet. Despite of the dependence of t_{us} on t_t and K (Equation 4), the means \mathbb{E} and thus
24 the Sobol indices do not follow the simple relationship because of Jensen's inequality (Jensen et al., 1906): $\xi = K$ is
25 a random variable and $f(\xi) = \frac{1}{\xi}$ is a convex function, thus $f(\mathbb{E}(\xi)) \leq \mathbb{E}(f(\xi))$.

26 From the previous observations, the flow field parameter causing the largest variance is the matrix inflow temperature
27 T_{in} , whereas the most dominant droplet initial condition is the deviation from the centerline r_d . Together, they account
28 for more than 50 % of variance in all quantities of interests. Therefore, a reduction of the uncertainty of the matrix
29 inflow temperature T_{in} and a reduction of the offset from the centerline r_d promise to have the biggest impact to

1 improve the precision of the experiment.
2 The sensitivity analysis was also performed for the B1 fuel, since it may be sensitive to different input variables.
3 However, the results are very similar, with only slight shifts from r_d to T_{in} for K and t_t . This shift can be explained
4 by the faster evaporation of B1 and thus the evaporation happening closer to the matrix heater.

5 8. CONCLUSIONS

6 In the present work, the evaporation of multi-component jet fuels was successfully studied using a combination
7 of experiments and numerical simulations with a detailed uncertainty quantification. The evaporation test case for
8 multi-component fuel droplets of realistic size provides precise measurements of droplet diameters over time. For all
9 tested fuels, the composition is well characterized and the difference of their evaporation behavior is measured with
10 high precision. The measurements of conventional and alternative jet fuels also capture the different stages of multi-
11 component evaporation behavior, such as droplet heating, fast evaporation of light components and slow evaporation
12 of heavy components.

13 Based on the results and boundary conditions of the measurements, the evaporation model was validated by means
14 of non-deterministic numerical simulations. The input uncertainties, introduced from boundary and initial conditions
15 of the experiment, were propagated through the model by non-intrusive non-deterministic simulations. Furthermore,
16 uncertainties associated with the estimation of the unknown boundary conditions were propagated. The uncertainty
17 quantification revealed that for all fuels modeled with the DCM the experimental data is within the probabilistic
18 bounds. In contrast, for two of the three multi-component fuels the measurement data were outside the predicted
19 intervals after 65 vol % had evaporated. As input uncertainties are propagated through the simulation, the deviation
20 has to be attributed to an error in the CTM evaporation or property model. This error shows that an examination of
21 the CTM evaporation model uncertainties is necessary, but is beyond the scope of the present study. Additionally, the
22 close agreement of the binary B1 fuel mixture's calculations with the experiment confirms the assumption of rapid
23 mixing inside the droplet. The sensitivity analysis reveals that the majority of variance in all quantities of interest is
24 related to the uncertainties in the matrix inlet temperature and the offset of the droplets from the centerline.

25 To conclude, the test case provides suitable validation data for aviation-relevant fuels. However, the UQ shows that
26 the uncertainties from uncharacterized boundary conditions are not negligible. From the findings of the sensitivity
27 analysis, the authors propose that the most promising enhancement for the validation experiment would be a reduction
28 of uncertainties in the matrix inlet temperature and in the reduction of the offset of the droplets from the centerline.
29 Finally, both the experiment and simulation profit from a close collaboration, as the non-deterministic approach gives

1 insight to sources of errors and provides quantitative data for the methodological improvement of the validation
2 experiment.

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9 for reliable numerical simulations.

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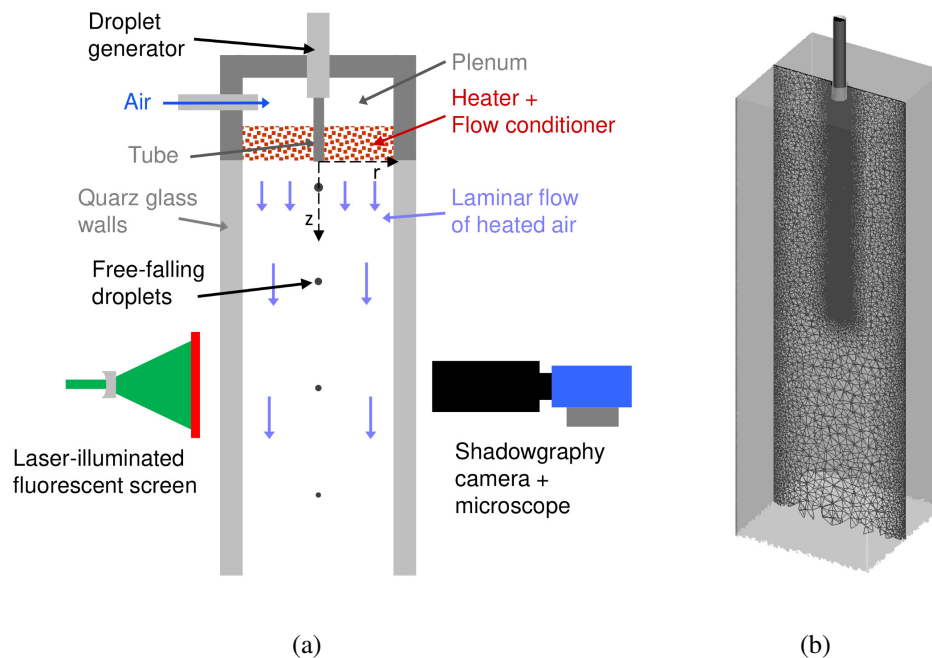


FIG. 1: Experimental Setup (a) and computational domain and depiction of the grid in a cut plane (b) of the droplet evaporation test case

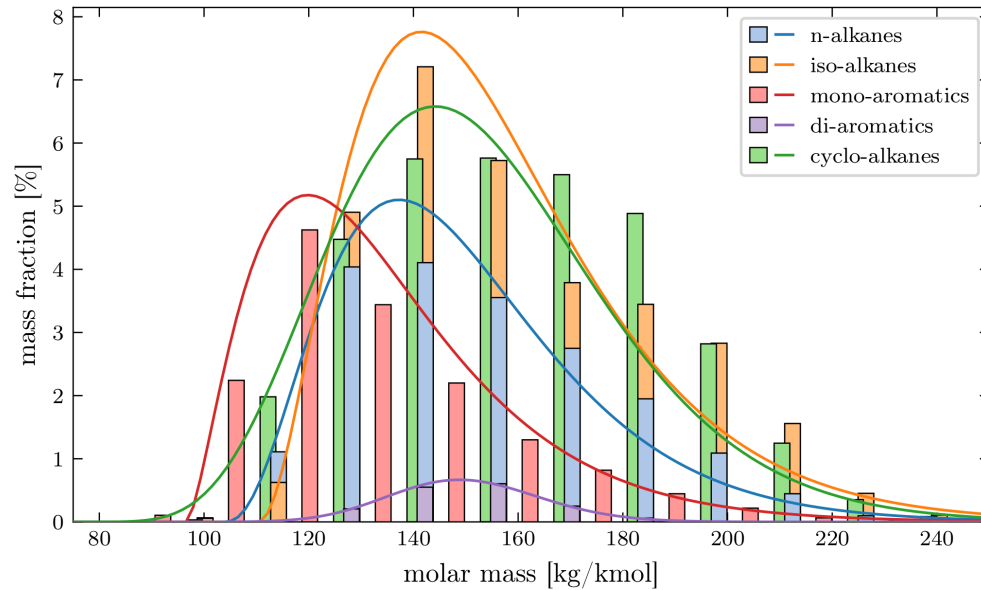


FIG. 2: Fuel composition for a conventional jet fuel clustered by fuel families. Bars indicate the discrete composition, lines the fitted composition by gamma distribution.

TABLE 1: Molar fractions of fuel families of multi-component jet fuels.

Name		n-alkanes	iso-alkanes	mono-aromatics	di-aromatics	cyclo-alkanes
A1	Reference fuel	0.192	0.307	0.155	0.017	0.329
B1	Alcohol-to-Jet	0.000	1.000	0.000	0.000	0.000
C1	High aromatic	0.101	0.150	0.019	0.181	0.549
C5	High volatility	0.110	0.166	0.105	0.118	0.501

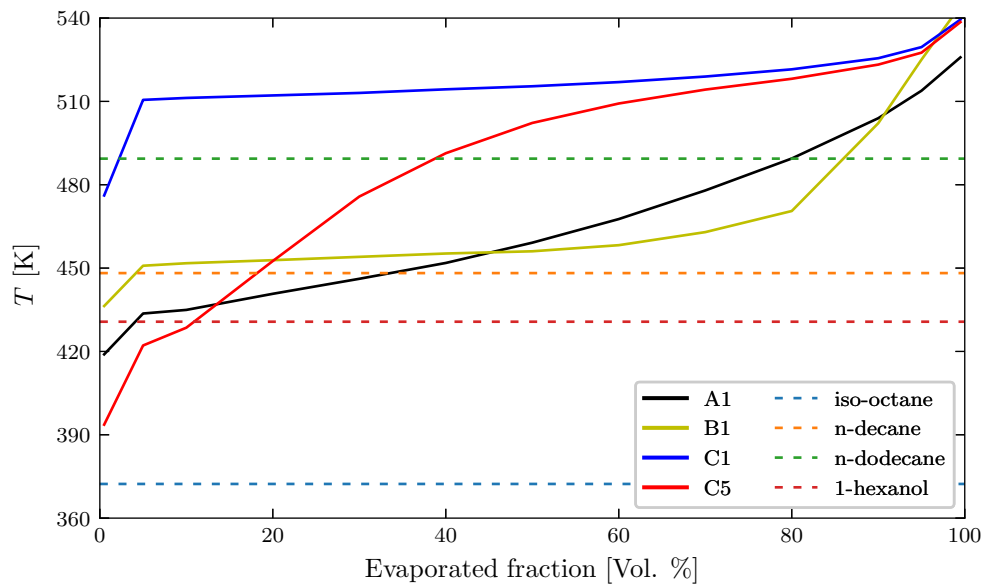


FIG. 3: Distillation curves of multi-component fuels using ASTM International (2004) D86 method (solid lines) and boiling points of single-component fuels (dashed lines) (Kim et al., 2019)

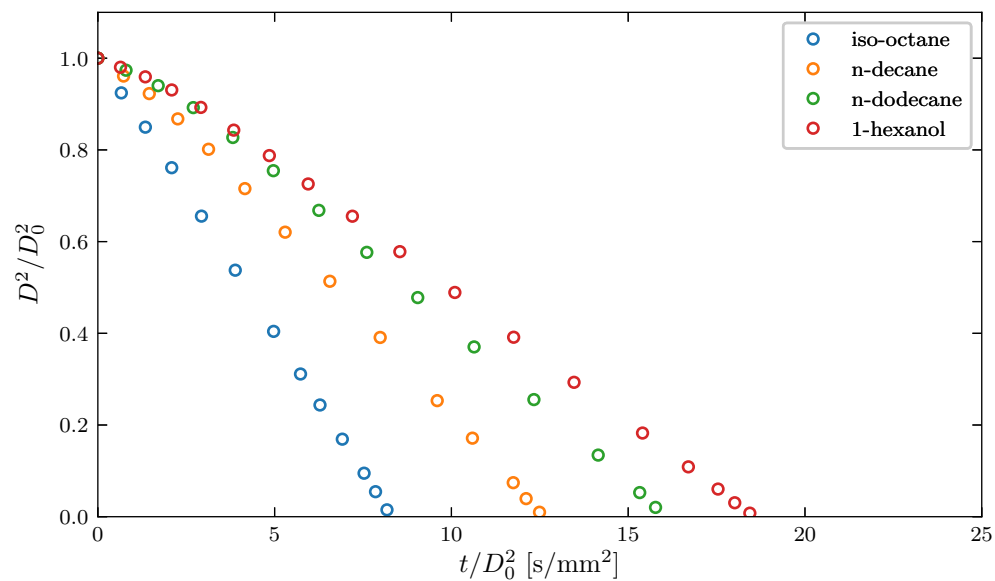


FIG. 4: Experimental results of single component fuels: Temporal evolution of squared droplet diameter D^2 , normalized by the squared initial diameter D_0^2 . Absolute errors are smaller than $0.01 \mu\text{m}^2/\mu\text{m}^2$ and thus not shown.

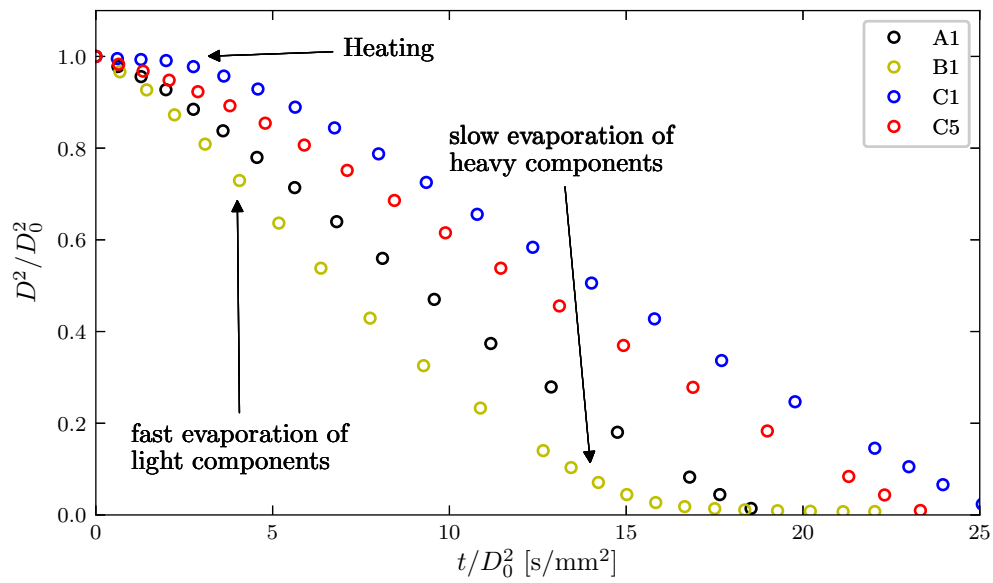


FIG. 5: Experimental results of multi-component fuels: Temporal evolution of squared droplet diameter D^2 , normalized by the squared initial diameter D_0^2 . Absolute errors are smaller than $0.01 \mu\text{m}^2/\mu\text{m}^2$ and thus not shown.

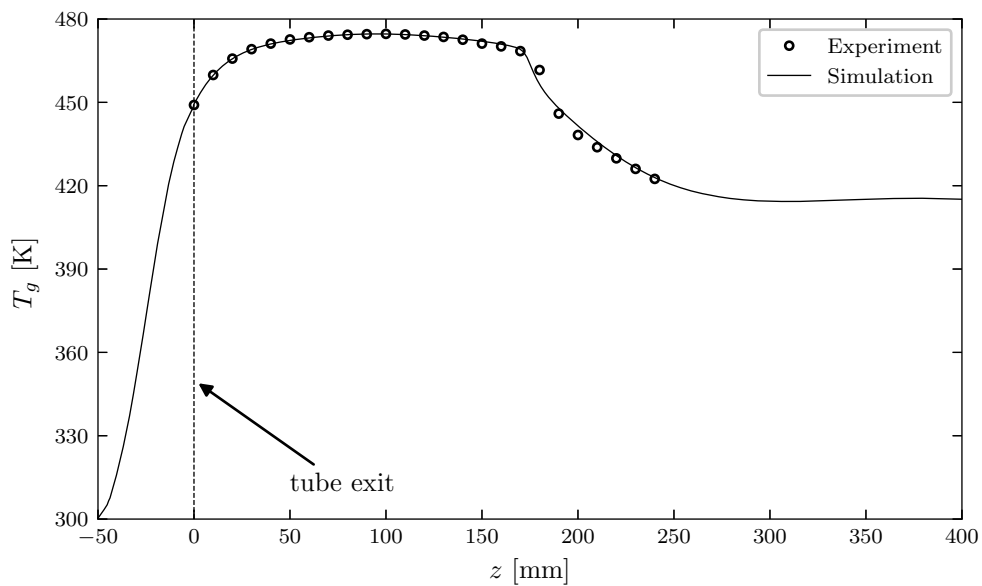
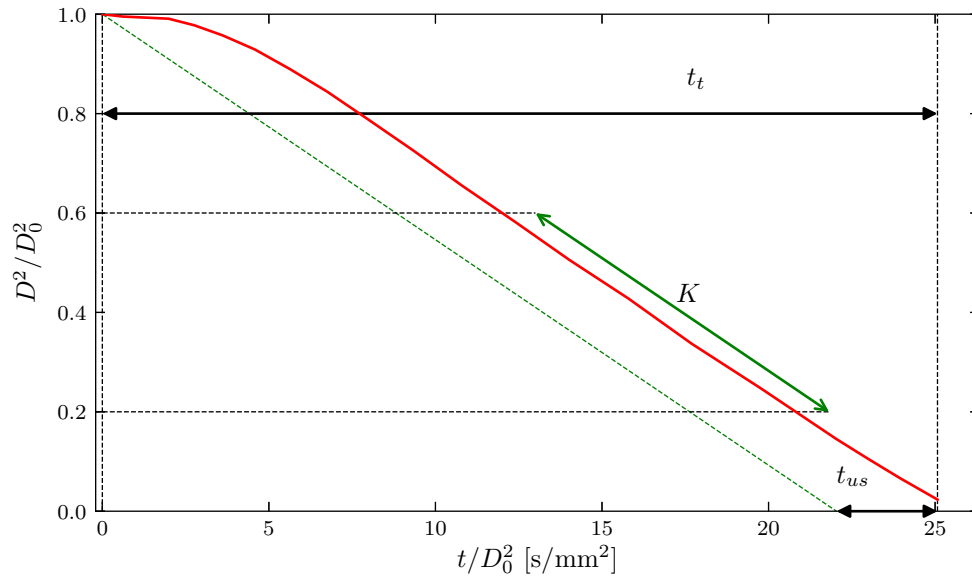


FIG. 6: Centerline profiles of ambient gas temperature $T_g(z)$

TABLE 2: Classification of the boundary conditions by type of method used to determine the values and corresponding uncertainties.

Boundary Condition			Determination method	Value	Uncertainty
Flow	Channel wall temperature at $z = 0$ mm	T_0	estimated by num. sim.	460 K	± 15 K
	Channel wall temperature at $z = 100$ mm	T_{100}	estimated by num. sim.	305 K	+15 K, -10 K
	Channel wall temperature at $z = 200$ mm	T_{200}	estimated by num. sim.	300 K	+15 K, -5 K
	Matrix Inflow temperature	T_{in}	thermocouple	478 K	± 5 K
	Tube wall temperature	T_t	estimated by num. sim.	470 K	± 5 K
Droplets	Droplet initial velocity	v_d	manufacturer's specs	2.0 m/s	± 0.2 m/s
	Droplet initial diameter	D_d	manufacturer's specs	80 μ m	± 2 μ m
	Droplet initial temperature	T_d	thermocouple	303.15 K	± 1.15 K
	Droplet initial centerline distance	r_d	shadowgraphy	0 mm	+ 1.8 mm


FIG. 7: Evaporation metrics: Total evaporation time t_t , evaporation rate K and unsteady heat-up time t_{us} , adapted from Asrardel et al. (2019)

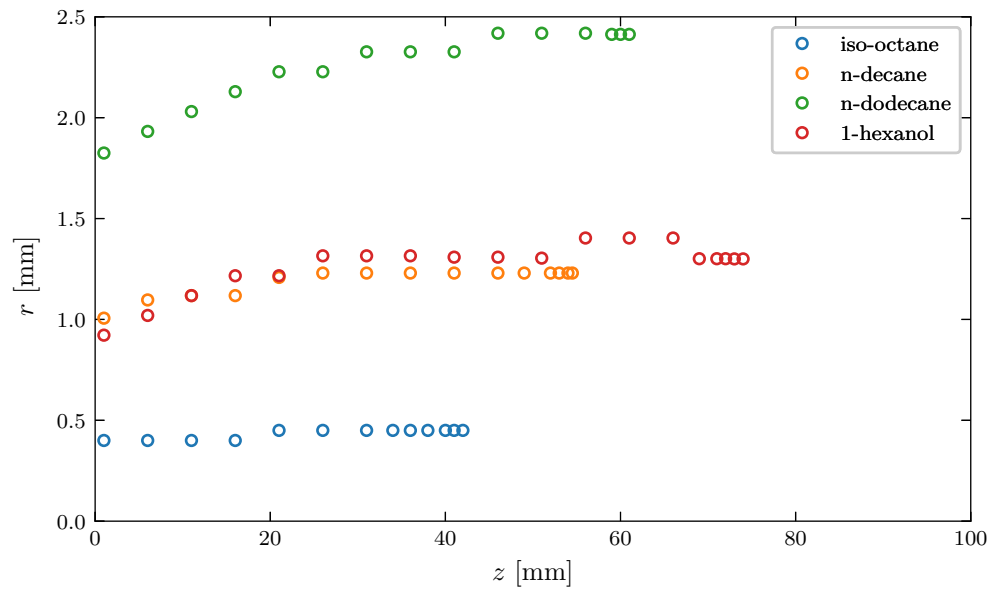


FIG. 8: Experimental results for the radial offset r of the droplets from the centerline ($r = 0$ mm)

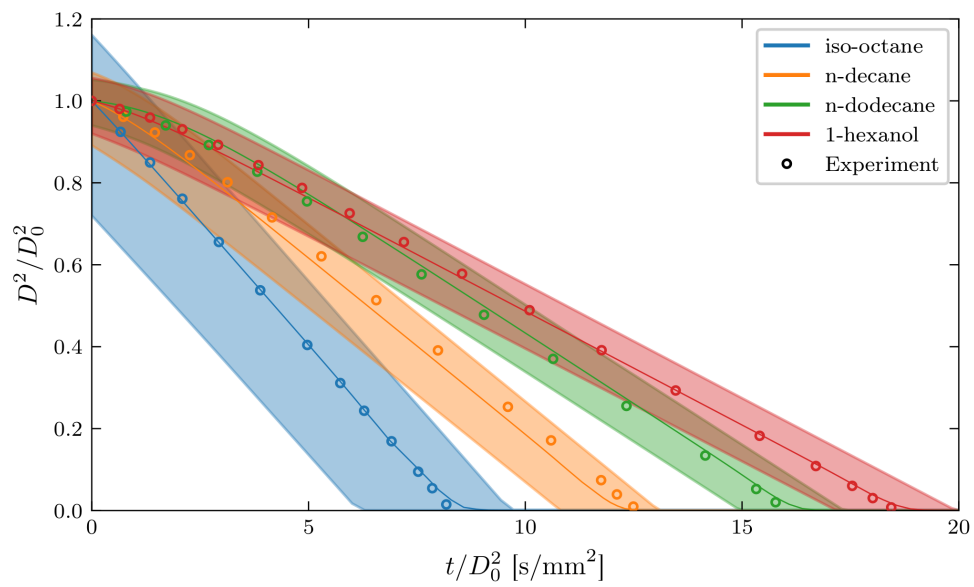


FIG. 9: Comparison of measurements (symbols) and non-deterministic simulations for single component fuels. Solid lines represent the mean \mathbb{E} , shaded areas the uncertainties.

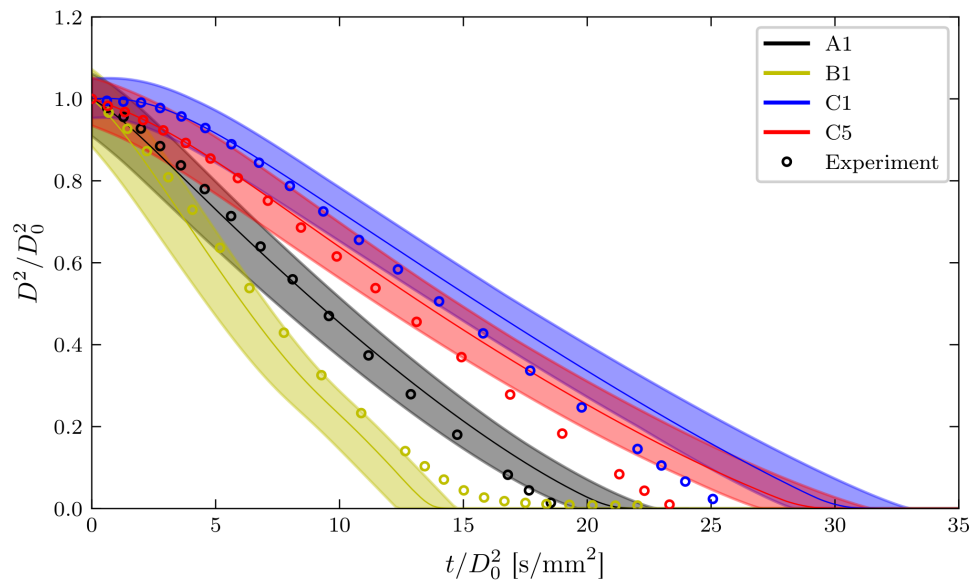


FIG. 10: Comparison of measurements (symbols) and non-deterministic simulations for multi-component fuels. Solid lines represent the mean \mathbb{E} , shaded areas the uncertainties.

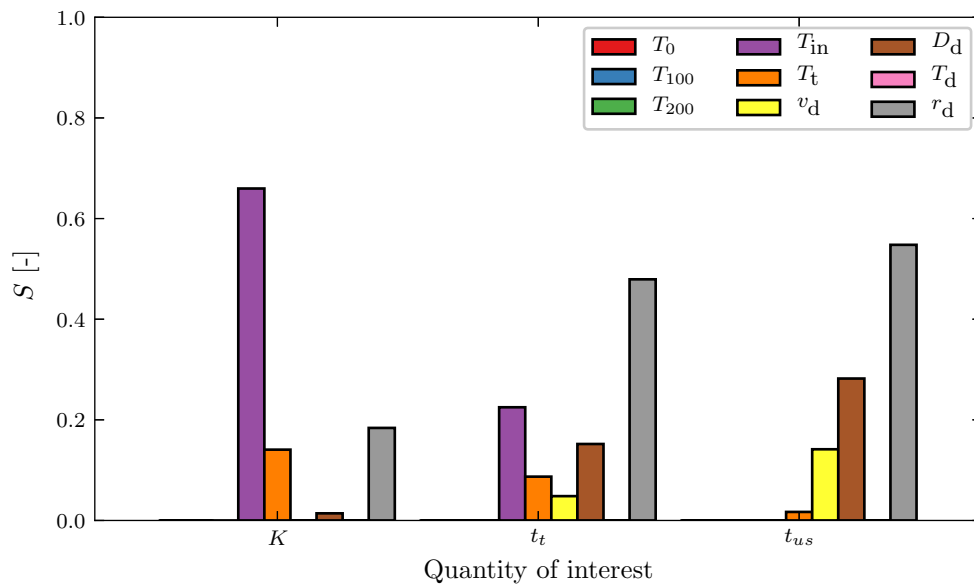


FIG. 11: Main Sobol indices S_i for the evaporation rate K , total evaporation time t_t and unsteady heat-up time t_{us} . The total Sobol indices S_i^T are nearly identical to the main indices and thus not shown.