

COMPUTATIONAL METHODOLOGIES  
FOR THERMAL RADIATION MODELING

By

NICOLAS TRICARD

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Computational Thermal Fluids Lab  
Department of Mechanical Engineering  
School of Engineering  
University of Connecticut  
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Insert acknowledgements here.

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## ABSTRACT

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# Chapter One

## Introduction

Over 80% of energy produced on earth is produced through combustion. Adequate understanding of combustion requires modeling of thermal radiation in order to capture the high heat flux values transported through the domain.

The seminal equation for thermal radiation is the Radiative Transfer Equation (RTE), eq. ??.

$$\frac{dI}{ds} = \dot{s} \div I \quad (1.1)$$

### 1.1 Motivation

The immense computational expense required for integration of the multitude of coupled equations within a combustion simulation are infeasible even with modern computing resources. In particular, radiation becomes prohibitive due to its all-to-all nature.

In attempt to maximize accuracy at the limitations of present resources, a number of models have been introduced to reduce the computational burden of radiation modeling. Of those, many involve complex mathematical assumptions and simplifications which can be difficult to learn, account for, and may lead to inaccurate results for many circumstances.

Of those, the Monte-Carlo Ray Tracing (MCRT) method stands out as the most robust.



MCRT is a direct physical interpretation of physical process by which the rays are transported through space. Within MCRT, random rays are initiated within the computational cells of the combustion simulation, and are tasked with traveling in a

## 1.2 Importance of soot and radiation in fire spread

## 1.3 Buoyancy-driven diffusion flames

## 1.4 Data-based approach

## 1.5 Organization

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# Models and Methods

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### 2.1.1 Soot formation

### 2.1.2 Soot growth and destruction

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Soot model expectations

Difficulties in soot modeling

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### 2.2.2 Review of soot research

### 2.2.3 Soot models used in the present work

Two-equation model

## 2.3 Soot modeling sensitivity

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## Ch3

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Kalman filter

Ensemble Kalman filter

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Previous studies

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## 4.2 Toy problem and parametric study

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## Conclusions and future work

### 6.1 Summary of findings



## APPENDICES

# Appendix A

## Data assimilation Supplementary Material

### A.1 Appendix Section 1

#### Temperature

Sample text

#### Soot volume fractions

Sample Text.

#### A.1.1 Assimilation of soot volume fraction measurements

Sample text

### A.2 Source term implementation

Sample text.

# Appendix B

## Machine Learning Supplementary Material

### B.1 Parametric study of the penalty coefficient

Sample text