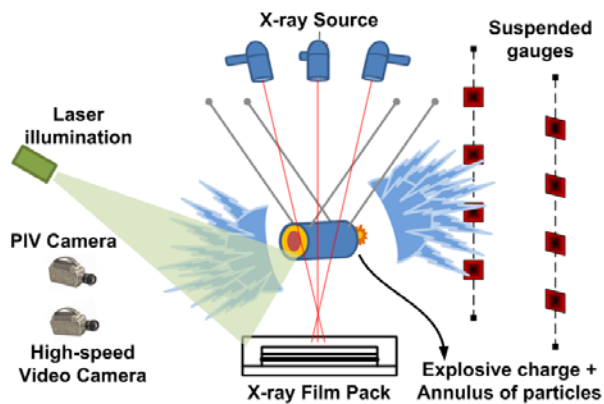


TST Review

October 30-31, 2017



CCMT

Internship Presentations

Paul Crittenden
Mohamed Gadou
Trokon Johnson
Yash Mehta



CCMT

Contact Front Instability and Code Verification

Lawrence Livermore National Laboratory

Spring 2017

Paul Crittenden

PhD Student
Mechanical and Aerospace Engineering Department
University of Florida



UF UNIVERSITY OF FLORIDA **Introduction**

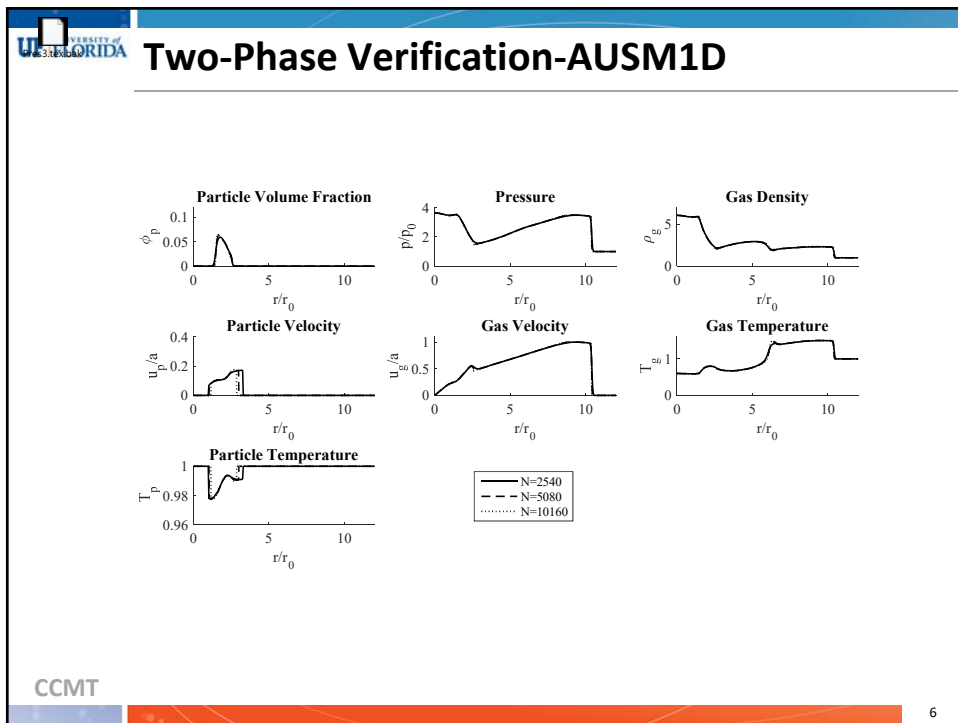
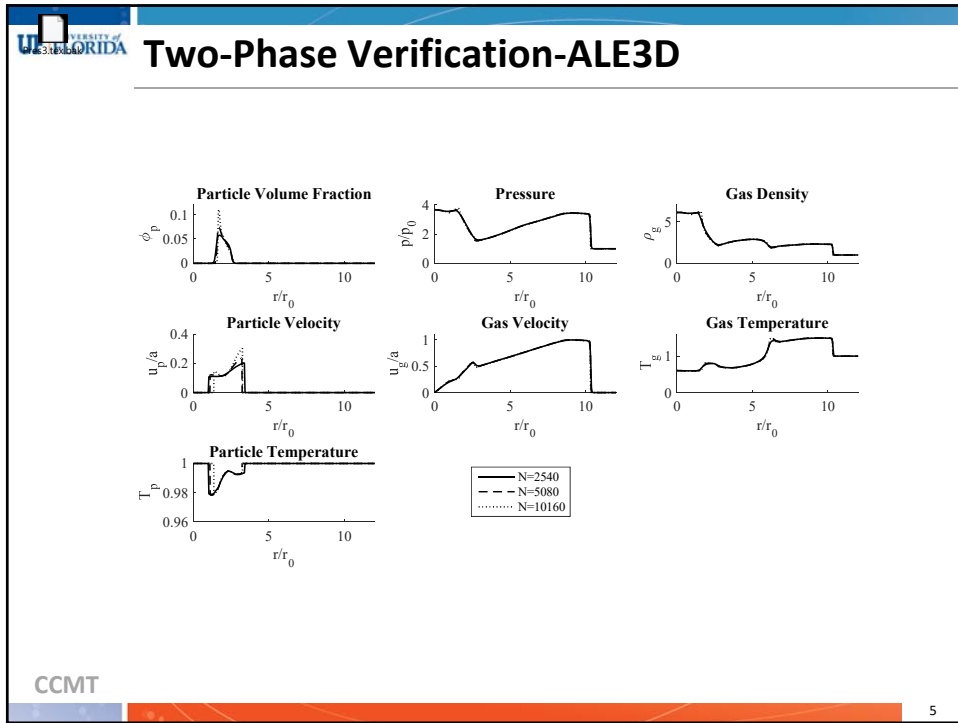
- Mentor Dr. Kambiz Salari (Sam Schofield, Tim Dunn)
- Worked on analytical stability results
- Ran shock tube test cases using ALE3D (Eulerian-Eulerian)
- ALE3D is a multi-physics numerical simulation software tool
- Main goal of the work was verification of my multiphase code

CCMT 3

UF UNIVERSITY OF FLORIDA **Single-phase Instability**

- Assumptions about contact (Epstein)
 - Spherical Harmonics
 - Spatially constant density
 - Irrotational base and perturbed flow
 - Equal compression rates (removed)
 - Incompressible perturbations

CCMT 4




UF UNIVERSITY OF FLORIDA **Activities at LLNL**

- Seminars
- End of internship presentation



CCMT 7

UF UNIVERSITY OF FLORIDA **Bay to Breakers!**




CCMT 8

CCMT

My Internship at LANL

Mohamed Gadou
Computer and Information Science and Engineering
University of Florida

- Mentors:
- Galen Shipman
- David Daniel
- Ryan Braithwaite



The bottom of the slide features three logos: the University of Florida logo on the left, the Department of Energy logo in the center, and the NASA logo on the right.

UF UNIVERSITY OF FLORIDA

Interning at The Lab

- Amazing environment for learning
- Organized workspace and excellent mentorship
- Opportunity for interacting with best minds in various Science fields
- Great Friendly and Helpful coworkers
- Aligned Values to Personal Values (Integrity, Safety, Security, Respect, ..)

CCMT

10

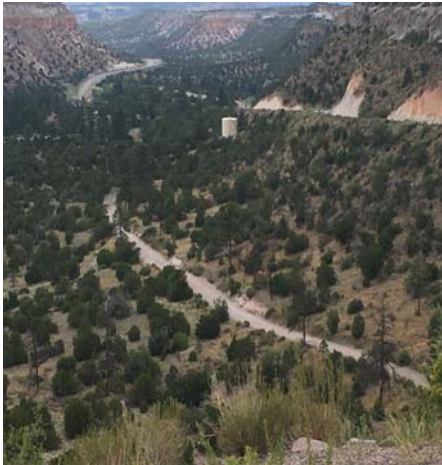
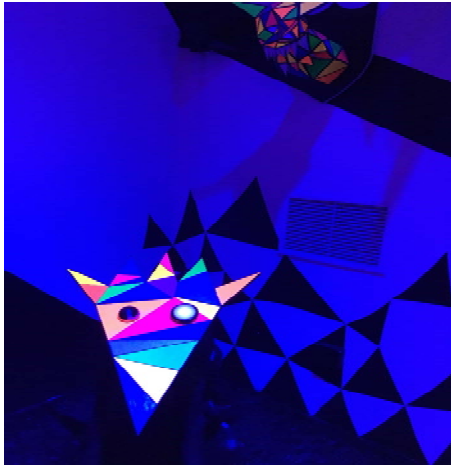
UF UNIVERSITY OF FLORIDA **Architecture Description**

■ Measuring Performance, Power, and Energy

Name	Description
IBM Power 8 + P100	<ul style="list-style-type: none"> - IBM power8 server with 2 sockets - Reported TDP of 190 watts per socket - NVLink to reduce data transfer overhead between CPUs/GPUs - 2 Nvidia Tesla P100 GPUs
Intel Broadwell – 2 sockets	<ul style="list-style-type: none"> - Intel Broadwell family E5 with 2 sockets - TDP of 135 watts per socket
Intel Haswell + K80	<ul style="list-style-type: none"> - Intel Haswell family E5 with 2 sockets - TDP of 120 watts per socket - 2 of ½ NVIDIA Tesla K80 GPUs
Intel KNL	<ul style="list-style-type: none"> - Intel Knights Landing with 72 cores - High Bandwidth memory is available (MCDRAM) - Multiple MCDRAM Configurations - MCDRAM size is 16 GB

CCMT 11

UF UNIVERSITY OF FLORIDA **Life at Los Alamos**


CCMT 12

CCMT

LANL PCSRI: Toward Parallelized Dictionary Learning and Sparse Coding

Trokon Johnson, The University of Florida

Mentors:
Cristina Garcia Corona (CCS-3)
Brendt Wohlberg (T-5)



The slide features a blue vertical bar on the left with the text 'CCMT'. The main content is centered on a white background. At the bottom, there is an orange horizontal bar containing the logos for the University of Florida, the Department of Energy, and NASA.


UF UNIVERSITY OF FLORIDA

Overview: Parallel Computing Summer Research Institute

- 10 Week Program
 - Crash Course of HPC Topics
 - MPI
 - Vectorization
 - Scrum
 - Quantum Computing
 - Special Projects
 - Small group projects for the duration
 - Contacts
 - Experts in different HPC areas

CCMT

| 14



Project: SPORCO Acceleration

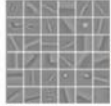


- Goal:
 - Sparse Coding: efficiently represent signals using dictionaries
 - can be used for denoising, feature identification, etc
 - Dictionary Learning: creates dictionary elements by training on signals
- Contribution
 - Parallelized existing convolutional dictionary learning library (SPORCO)
 - mpi4py
- Impact
 - Significant reduction in time to create trained dictionary elements
 - Allows for largest convolutional dictionary problem solved, to our knowledge

Sparse Coding

$$\arg \min_{\{x_m\}} \frac{1}{2} \left\| \sum_m d_m * x_m - s \right\|_2^2 + \lambda \sum_m \|x_m\|_1$$

Dictionary Update


$$\arg \min_{\{d_m\}} \frac{1}{2} \sum_k \left\| \sum_m d_m * x_{k,m} - s_k \right\|_2^2$$



*

=


Dictionary, D
12x12x36=5184

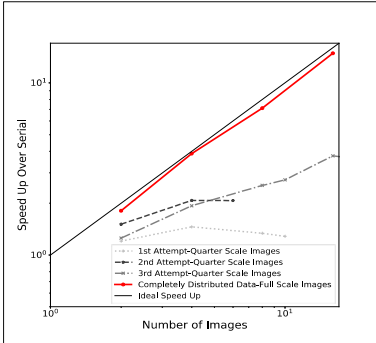
Sparse
Representation
x

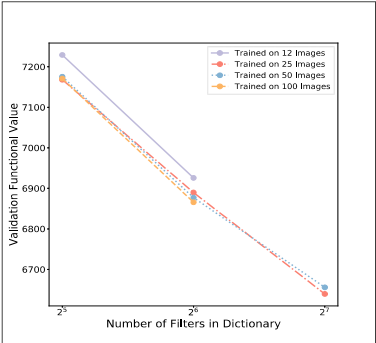
Signal, S
1024x1024=1048576


| 15




Results






- Great weak scaling results
- Allowed for much larger tests
 - 256x256 -> 1024x1024
 - 100 Images



| 16

UF UNIVERSITY OF FLORIDA **Excursions**



17

UF UNIVERSITY OF FLORIDA **Excursions, pt. 2**



CCMT

18




CCMT


Shock Interaction with Moving Particles

Lawrence Livermore National Laboratory

Summer 2017

Yash Mehta
PhD Student
Mechanical and Aerospace Engineering Department
University of Florida

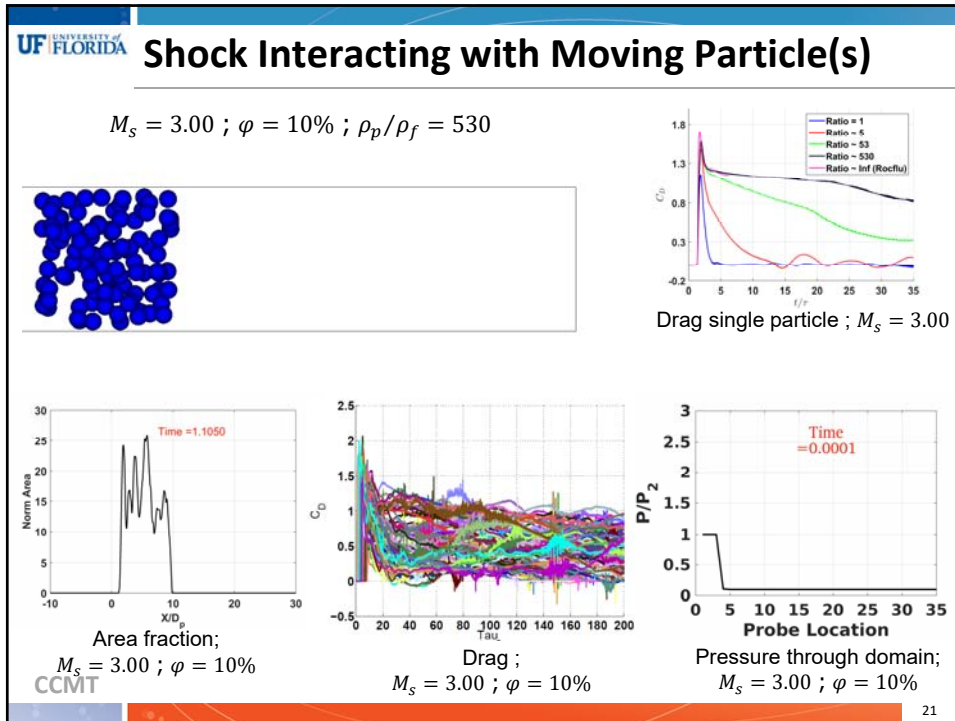
  

 **Introduction**

- Mentor Dr. Kambiz Salari
- Worked on analyzing data from ALE3D simulations
- ALE3D is a multi-physics numerical simulation software tool using arbitrary Lagrangian-Eulerian (ALE) techniques
- Main goal of the work was to understand motion of multiple particles under detonation conditions

CCMT

20



Activities at LLNL

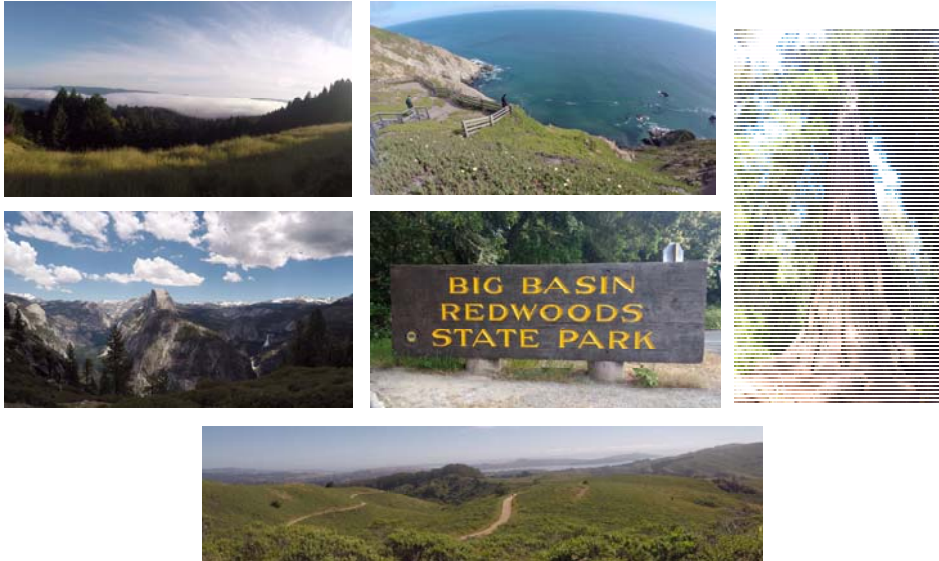
- NIF tour
- Summer Interns barbecue
- Summer seminar series (various programs)
- Computation program – “Apple Time”
- Computation seminar – end of internship presentation



CCMT

22


UF UNIVERSITY OF FLORIDA **Life around Livermore**




CCMT 23

CCMT

Do you have any questions?




UF UNIVERSITY OF FLORIDA  **NASA**

CCMT

Surrogate Modeling of the JWL Equation of State

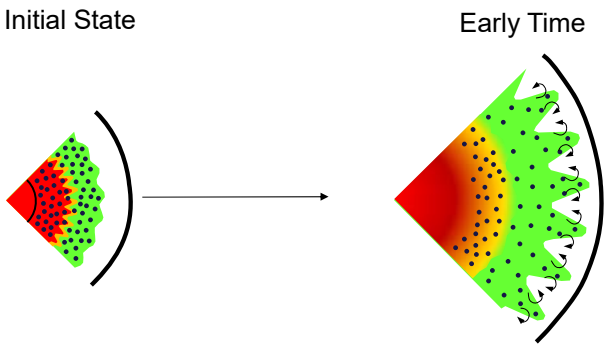
Frederick Ouellet
PhD Student



The slide features a blue vertical bar on the left with the text 'CCMT'. The main title is 'Surrogate Modeling of the JWL Equation of State' by 'Frederick Ouellet, PhD Student'. At the bottom, there is an orange bar containing the logos for the University of Florida, the Department of Energy, and NASA.

UF UNIVERSITY OF FLORIDA **Goal – Handling Cells with Mixed E.O.S.**


Initial State Early Time



- A short time after detonation, there are both pure explosive products and pure air
- At later time, pure species still exist but a mixture region will form where two equations of state must be satisfied
- Goal is to find a way to simplify and speed up the gas computations in this zone

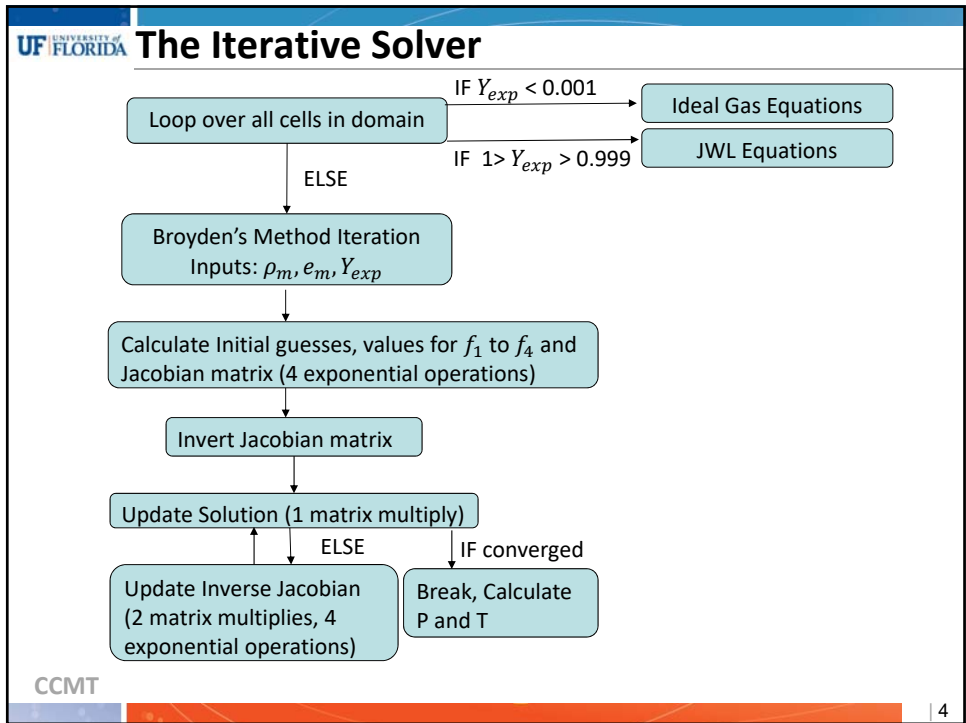
CCMT | 2

The diagram shows a detonation front moving from left to right. The 'Initial State' shows a sharp front with a red region (explosive) and a green region (air). The 'Early Time' state shows the front has become more complex, with a red region, a green region, and a yellow region (mixture) between them. The front is now wavy and irregular.

 Standard Approaches for Mixed Cells		
Method of Tackling	Pros	Cons
Mass fraction weighted averaging	<ul style="list-style-type: none"> Algebraic equations Small data storage 	<ul style="list-style-type: none"> Does not place species equilibrium requirement
Tabulated data	<ul style="list-style-type: none"> Interpolation is only operation Can place species equilibrium requirement 	<ul style="list-style-type: none"> Must store the tabulated data Interpolation error
Polynomial regressions/curve fits	<ul style="list-style-type: none"> Algebraic equations Small data storage Can place species equilibrium requirement 	<ul style="list-style-type: none"> Curve fit errors
Iterative schemes	<ul style="list-style-type: none"> Small data storage Can place species equilibrium requirement 	<ul style="list-style-type: none"> Computationally expensive

➤ Rocflu uses a Broyden's method iterative solver to enforce pressure and temperature equilibrium between air and the explosive products

CCMT | 3



UF UNIVERSITY OF FLORIDA **Looking at the Big Picture**

> What is an iterative scheme really doing?

Inputs:
 ρ_m, e_m, Y_{exp}

↓

Outputs:
1) Common pressure/temperature for both EoS
2) Internal energy attributed to the air and the products
3) Density attributed to the air and the products

> If we compute the common pressures and temperatures outside of the code, a curve fit can be applied

CCMT | 5

UF UNIVERSITY OF FLORIDA **Models Implemented in Rocflu**

The Jones-Wilkins-Lee (JWL) equations of state are used to predict the pressures of high energy substances and are:

$$P_{JWL}(\rho, e) = A\left(1 - \frac{\omega}{R_1 V}\right)e^{-R_1 V} + B\left(1 - \frac{\omega}{R_2 V}\right)e^{-R_2 V} + \omega \rho e$$

$$T_{JWL}(P, \rho) = \left(\frac{1}{\rho \omega C_v}\right)(P - A e^{-R_1 V} - B e^{-R_2 V})$$

where $V = \frac{\rho_0}{\rho}$ and $\rho_0, A, B, C, R_1, R_2$ and ω are parameters for the substance.

	Iterative Method	One Equation Model	Multi-Fidelity Surrogate
Advantages	<ul style="list-style-type: none"> - Accuracy - Problem independent 	<ul style="list-style-type: none"> - Speed - Algebraic equation 	<ul style="list-style-type: none"> - Speed - Accounts for species equation
Disadvantages	<ul style="list-style-type: none"> - May be slow to converge - Computationally expensive 	<ul style="list-style-type: none"> - Uncertainty and error - JWL + ideal gas case only 	<ul style="list-style-type: none"> - Uncertainty - Equation of State specific (problem specific)
Used In	HR 2	HR 3/4/5	Future HRs

CCMT | 5

Surrogate Model - Development

- Kriging method used to generate two models for mixed cell pressure and temperature in terms of ρ_m , e_m and Y_{exp} using 50-800 sampling points
- Domain Space: $\rho_m \rightarrow (1, 1770)$
 $e_m \rightarrow (1.25e5, 1.5e7)$
 $Y_{exp} \rightarrow (0, 1)$
- Average relative errors (for 200 point model):
 - Pressure: 1.298%
 - Temperature: 0.132%

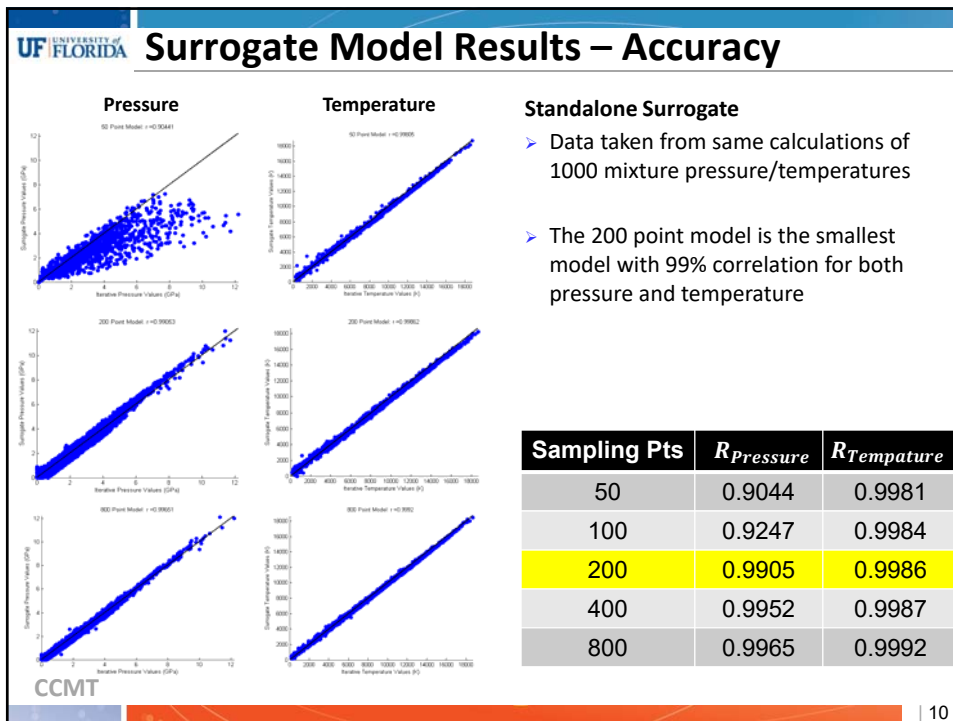
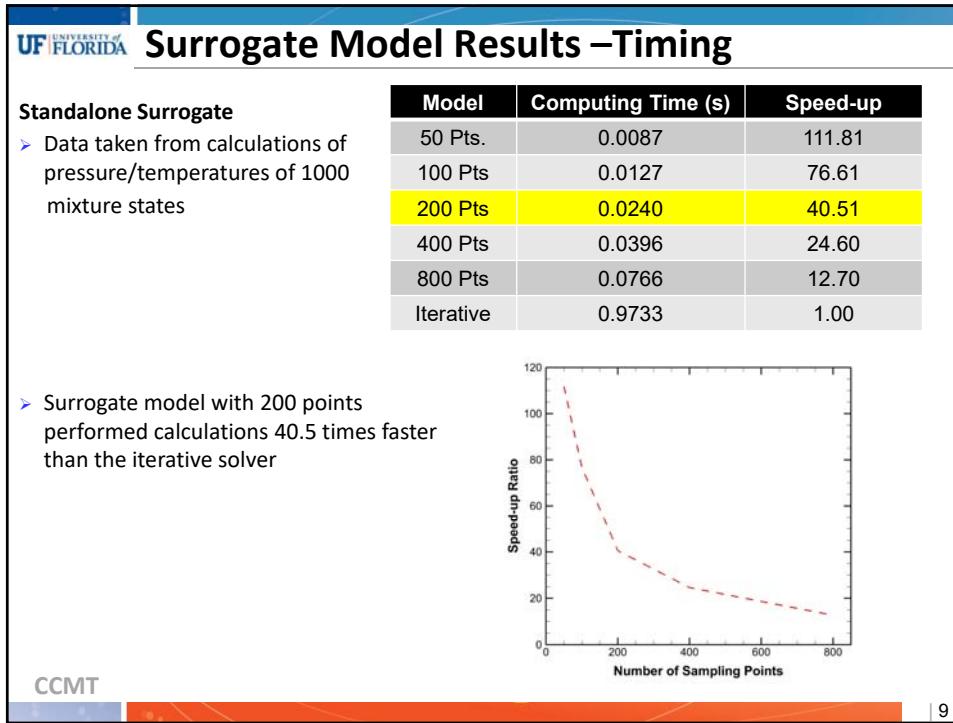
CCMT | 7

Flowchart – Iterative vs. Surrogate

```

    graph TD
      Start([Loop over all cells in domain]) -- "IF Y_exp < 0.001" --> IG[Ideal Gas Equations]
      Start -- "IF 1 > Y_exp > 0.999" --> JW[JWL Equations]
      Start -- ELSE --> BM[Broyden's Method Iteration  
Inputs: rho_m, e_m, Y_exp]
      BM --> Calc[Calculate Initial guesses, values for f_1 to f_4 and  
Jacobian matrix (4 exponential operations)]
      Calc --> Inv[Invert Jacobian matrix]
      Inv --> Upd[Update Solution (1 matrix multiply)]
      Upd --> InvJac[Update Inverse Jacobian  
(2 matrix multiplies, 4 exponential operations)]
      InvJac --> Upd
      InvJac -- ELSE --> BM
      InvJac -- IF converged --> Break[Break, Calculate P and T]
      Break --> BM
      BM --> SM[Surrogate Model  
Inputs: rho_m, e_m, Y_exp]
      SM --> Read[Read in fit parameters]
      Read --> Call[Call model operations twice  
(2 matrix multiplies, n_pts exp. operations each)]
      Call --> Out[Output P and T]
  
```

CCMT | 8



Simulation Results – Timing

- Simulation is run until first appearance of a species mixture cell
- 1000 time steps are run for each EoS model to gather timing data
- Process is repeated five times and averaged
- Notable code speed-up factor:
 - 200 points: 2.63

Simulation Description

- 2D, Cylindrical grid
- Outer radius = 0.3 m
- 400,000 cells
- Gas-Only

Number of Sampling Points	Speed-up Ratio
50	3.1
100	2.8
200	2.63
400	2.3
800	1.8

CCMT
| 11

Simulation Results – Accuracy

- Maximum errors in blast wave location:
 - 50 points: 6.85%
 - 200 points: 0.83%
 - 800 points: 0.35%

Simulation Description

- 2D, Cylindrical grid
- Outer radius = 0.3 m
- 400,000 cells
- Gas-Only

- Maximum errors in peak pressure:
 - 50 points: 14.06%
 - 200 points: 8.52%
 - 800 points: 3.41%

CCMT
| 12

UF UNIVERSITY of FLORIDA **Conclusions and Future Work**

Conclusions:

- Surrogate models allow for faster computations of the equation of state in mixture cells
- The models produce results that approach the iterative scheme given a sufficient number of sampling points in the input space

Future Work:


- **Multiple Species:**
 - Using an iterative solver, this means going from a 4×4 system of equations to an $2n \times 2n$ system of equations
 - As long as the same number of sampling points are used to create a new surrogate, the computation time would remain fixed
- **Multiphase Flows:**
 - Tests to verify that shifting to the surrogate models does not impact the particle metrics
- Paper in preparation with this work: F. Ouellet, C. Park, B. Rollin, R. T. Haftka and S. Balachandar: A Multi-Fidelity Surrogate Model for Handling Gas Mixture Equations of State

CCMT | 13

CCMT

Do you have any questions?

This work was supported by the U.S. Department of Energy, National Nuclear Security Administration, Advanced Simulation and Computing Program, as a Cooperative Agreement under the Predictive Science Academic Alliance Program, under Contract No. DE-NA0002378.

UF UNIVERSITY of FLORIDA  **NNSA**

CCMT

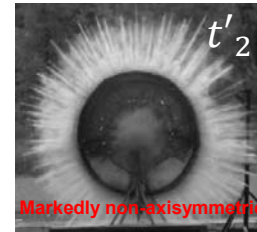
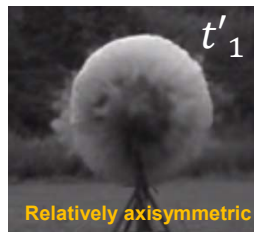
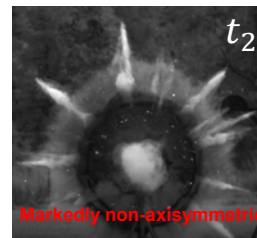
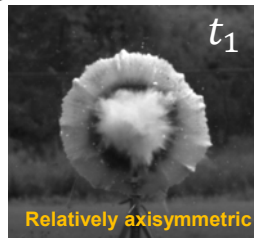
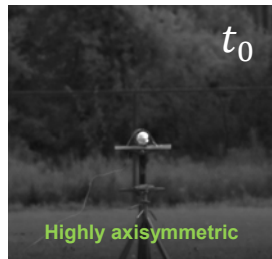
Surrogate-Based Optimization for Exploring the Physics in Explosive Dispersal of Particles

M. Giselle Fernández-Godino
PhD Student (UB-Physics)



UF UNIVERSITY OF FLORIDA

Departure from Axisymmetry

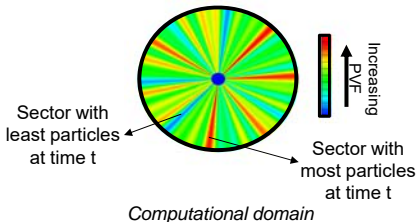


CCMT

2

Questions

- What is a good metric of **departure** from **axisymmetry**?
 - Difference between the Particle Volume Fraction (PVF) of the sector with most particles and the one with least.



- Which **initial disturbances amplify most** the departure?
 - Multimodal initial PVF perturbations
 - Optimization
 - Surrogate models


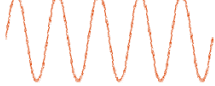

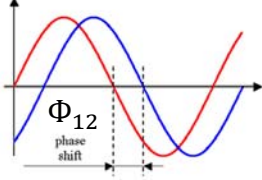



CCMT 3

Parametrization of Initial PVF Perturbation

$$\varphi^p(\theta) = \varphi_o^p [1 + A_1 \cos(k_1\theta) + A_2 \cos(k_2\theta + \Phi_{12}) + A_3 \cos(k_3\theta + \Phi_{13})]$$

Particle Volume Fraction (PVF) Base PVF

Design Variables

Wavenumber	Amplitude	Phase Shift
$k = 4$ 	A_1  A_2  $A_1 > A_2$	
$k = 6$ 		
$k = 8$ 		
$k = 16$ 		

CCMT 4

UF UNIVERSITY OF FLORIDA **Parametrization of Initial PVF Perturbation**

$$\varphi^p(\theta) = \varphi_o^p [1 + A_1 \cos(k_1\theta) + A_2 \cos(k_2\theta + \Phi_{12}) + A_3 \cos(k_3\theta + \Phi_{13})]$$

Single-modal Bi-modal Tri-modal

Effective $k = \frac{\sum_{i=1}^n k_i}{n}$ Effective $A = \sqrt{\sum_{i=1}^n A_i^2} = 0.1\sqrt{2}$

Wavenumber	Amplitude	Phase Shift
$k = 4$ $k = 6$ $k = 8$ $k = 16$	A_1 A_2 $A_1 > A_2$	Φ_{12} phase shift

CCMT 5

UF UNIVERSITY OF FLORIDA **Illustration from Simulations**

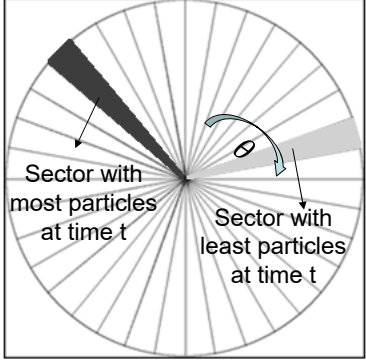
Single mode, $k = 10, A = 0.1\sqrt{2}$

$t=0s$ $t=100\mu s$ $t=300\mu s$

- Computational particles on top of density contours
 - Single mode, $k = 10, A = 0.1\sqrt{2}$
- Initial sinusoidal angular particle volume fraction (PVF) perturbations translate in finger like structures at later times
- Particles travel faster in sectors where PVF is initially lower

CCMT 6

Departure from Axisymmetry



Sector with most particles at time t

Sector with least particles at time t

Computational domain is divided in as many sectors as cells in θ

$$\zeta(t) = \text{Norm. Max. PVF Diff}(t) = \frac{[\text{Max}(PVF(\theta)) - \text{Min}(PVF(\theta))](t)}{[\text{Max}(PVF(\theta)) - \text{Min}(PVF(\theta))](t = 0)}$$

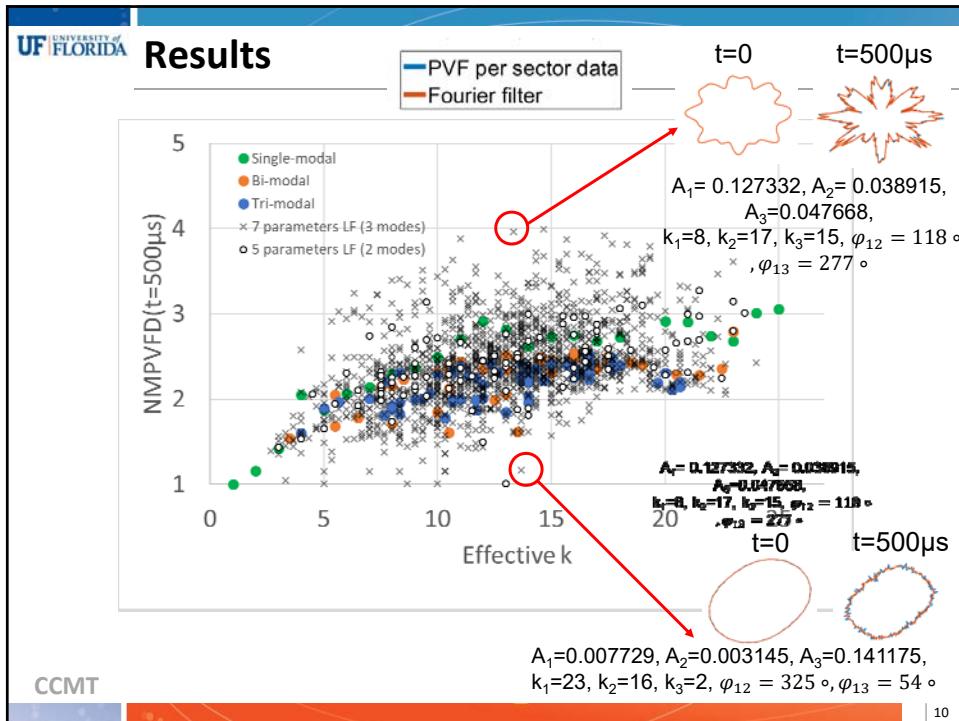
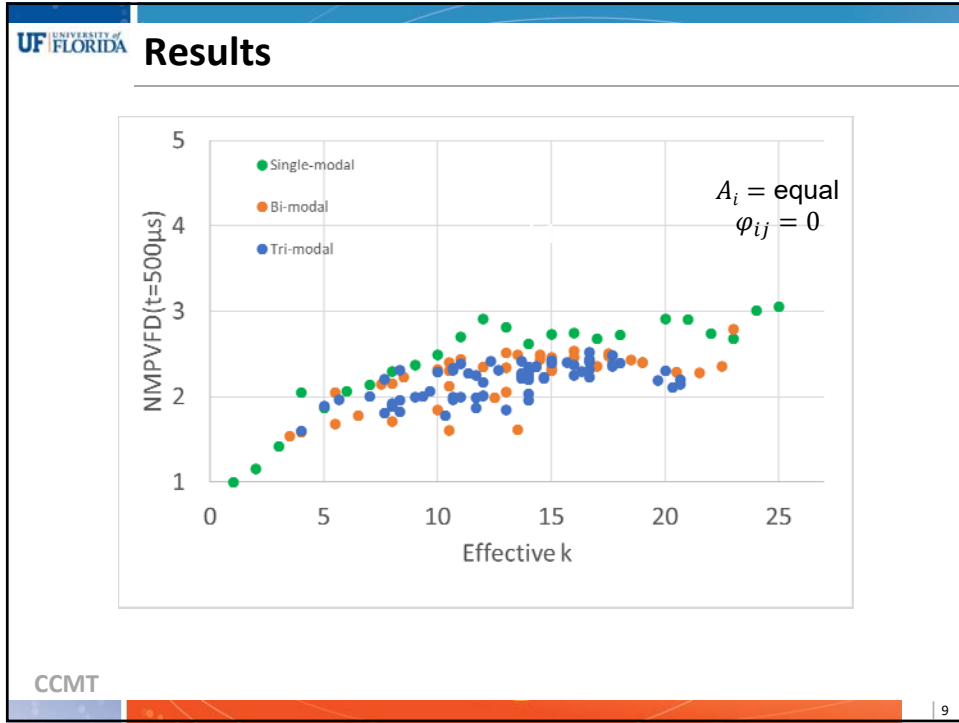
- PVF per sector = $\frac{\text{Volume of particles}}{\text{Volume of the sector}}$
- PVF of sector with most particles minus PVF of sector with least particles, divided by this difference at $t=0$ s
- This metric does not take into account radial variations

CCMT | 7

Runs: Summary

	# Runs LF/HF	Machine	Case	Individual Time LF/HF
	14/6	HPG	1 parameter	15h/24h
	40/40	HPG	2 parameters	6h/24h
	80/20	Quartz	3 parameters	6h/24h
	100/0	Quartz	5 parameters	6h
	1600/800	Quartz	7 parameters	6h/24h
TOTAL	1834/866			11,130h/20,784h

CCMT | 8



Surrogate based Optimization

$$\varphi^p(\theta) = \varphi_0^p [1 + A_1 \cos(k_1\theta) + A_2 \cos(k_2\theta + \Phi_{12}) + A_3 \cos(k_3\theta + \Phi_{13})]$$

↓

Design Variables

$\left. \begin{array}{l} \text{maximize } \text{Norm. Max. PVF Diff.} \\ A_1, A_2, A_3, k_1, k_2, k_3, \Phi_{12}, \Phi_{13} \end{array} \right\} \text{Objective Function}$

$\left. \text{Subject to } \sqrt{A_1^2 + A_2^2 + A_3^2} = \text{constant} \right\} \text{Energy Constraint}$


- ✓ LF (low-fidelity) is a reduced grid of about 0.25HF (high-fidelity) cost
- ✓ HFS (high-fidelity surrogate) fits HF alone, MFS (multi-fidelity surrogate) fits both together

CCMT | 11

Single Parameter Study (tri-modal pert.)

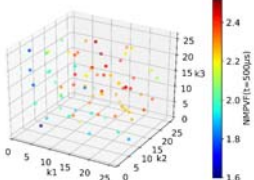
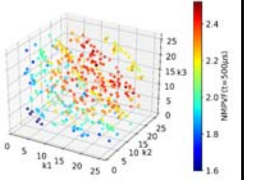
- Tri-modal perturbation
- **One variable**, k_1
- $k_2=15, k_3=25, A_1=A_2=A_3=0.1633, \Phi_{12}=\Phi_{13}=0$ remain constant
- Surrogate model obtained using **14 LF points**, **3 HF points** and 3 validation points
- The model is able to predict the validation points quite well just with a few HF points
- **General trend** : NMPVFD increases as k increases
- $k_1=5$ show a lower growth while $k_1=10$ a higher one. Important triadic interaction between modes!

CCMT | 12



3 Parameters Study (tri-modal pert.)


- Simplified problem: **Three variables**, k_1 , k_2 , and k_3
- $A_1=A_2=A_3=0.1\sqrt{2/3}$, $\Phi_{12}, \Phi_{13}=0$ remain constant
- **General trend**: NMPVFD increases with the effective k
- Preliminary Bayesian MFS is use to fit the MFS
- Mirror points reduce the CV error a 77%
- Mirror points are points with the same output. i.e. In this case wave numbers (2,4,3) has mirror points (2,3,4) (3,2,4) (3,4,2) (4,2,3) (4,3,2)

Left. LF data without mirror points (70 points). Right. LF data including mirror points (420=70x6).

CV not including mirror points	CV error including mirror points
0.186147	0.042238

CCMT
13



Conclusions and Future Work

- The future and main goal is **optimization** in 7 variables to find the initial disturbance producing **maximum departure from axisymmetry**
- We have obtained encouraging results using **multi-fidelity surrogate models** This will allow a reduced cost optimization
- We are finding interesting **interactions between the modes** imposed as a perturbation in the particle volume fraction at initial time

CCMT
14

CCMT

Thank you!
Do you have any
questions?

UF UNIVERSITY of
FLORIDA




NNSA

CCMT

Pairwise Interaction Extended Point-Particle (PIEP) Modeling

W. Chandler Moore



The slide features a blue vertical bar on the left with the text 'CCMT'. The main content is centered on a white background. At the bottom, there is an orange horizontal bar containing the logos for the University of Florida, the Department of Energy, and NASA.

UF UNIVERSITY OF FLORIDA

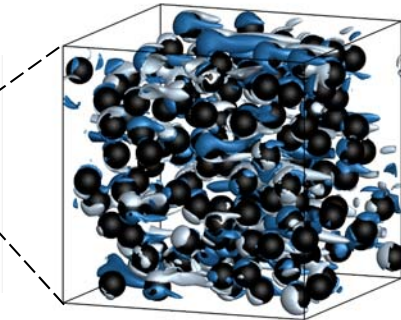
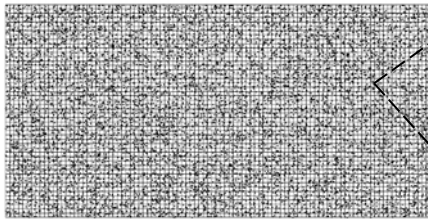
Outline

- Neighbors matter due to fluid-mediated Particle-Particle interactions
- Previously formulated PIEP model provides a rational approach to accounting for this fluid-mediated Particle-Particle interaction at low volume fractions
- The addition of a data-driven term greatly enhances the PIEP model at high volume fractions

CCMT | 2

Euler-Lagrange Approach

- Orders of magnitude faster than fully resolved simulations
 - EL & EE only viable approaches for practical problems
 - Point-particle models are needed for EL

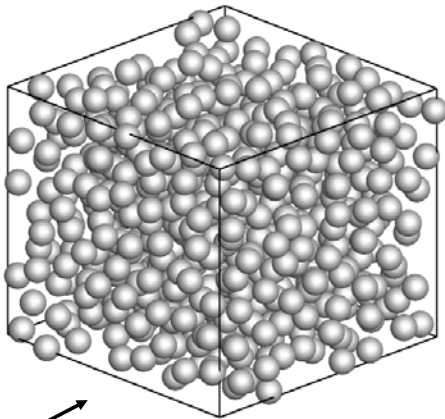


CCMT

3

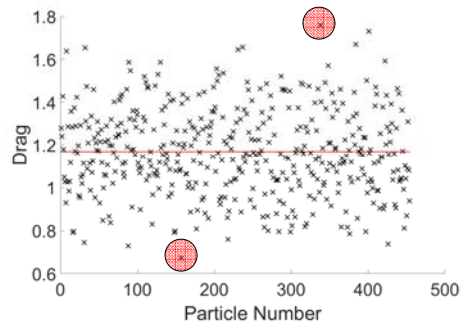
Fully Resolved Simulations

- Immersed boundary method, Grid = $(490)^3$, $d/\Delta x = 60$



$\phi = 44\%$, $Re = 20$, $N = 459$

CCMT

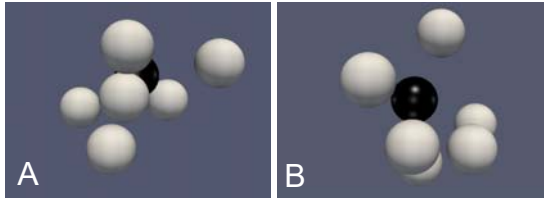
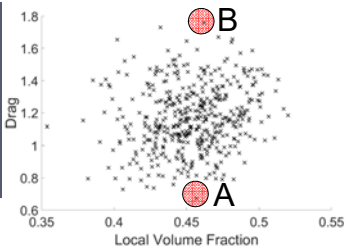


$$\frac{F_D}{F_{Sto}} = \frac{1 + 0.15Re^{0.687}}{(1 - \phi)^3} + \dots$$

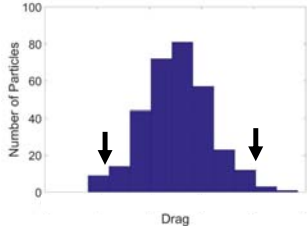
4

UNIVERSITY OF FLORIDA **Exact Location of Neighbors**

View as seen by Incoming Flow

Similar Local Volume Fraction



- Local volume fraction cannot explain the variations
- Upstream, downstream, lateral neighbors have different influence

CCMT

Akiki, Balachandar, JCP, 307, 34-59 (2016)
Akiki, Jackson, Balachandar, Phys Rev Fluids, 1, 044202 (2016)

5

UNIVERSITY OF FLORIDA **Current PIEP Model**

$$\mathbf{F}_{PIEP} = \mathbf{F}_{qs} + \mathbf{F}_{un} + \mathbf{F}_{am} + \mathbf{F}_{vu} + \mathbf{F}_L + \mathbf{F}_c$$

$$\mathbf{T}_{PIEP} = \mathbf{T}_{qs} + \mathbf{T}_{un} + \mathbf{T}_c$$

where, using perturbation maps resulting from direct numerical simulations (DNS),

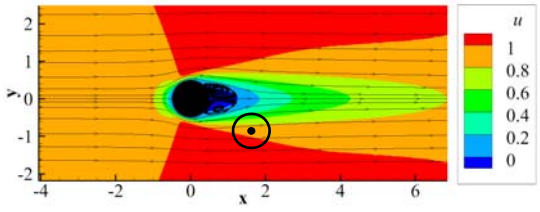
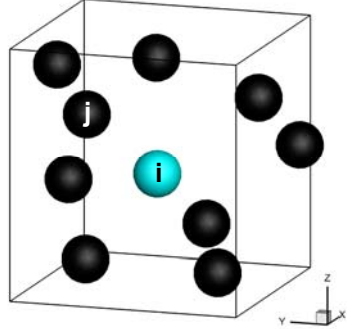
$$\mathbf{F}_{PIEP} \equiv \mathbf{F}_{PIEP}(Re, \phi, r_1, r_2, \dots, r_N, v_1, v_2, \dots, v_N)$$

$$\mathbf{T}_{PIEP} \equiv \mathbf{T}_{PIEP}(Re, \phi, r_1, r_2, \dots, r_N, v_1, v_2, \dots, v_N)$$

CCMT

6

Example: Quasi-Steady Force

$$\mathbf{F}_{qs,i} = \mathbf{F}_{ra}(\phi_i, Re_i) + \left\{ 3\pi \alpha d_i \left(\sum_{\substack{j=1 \\ j \neq i}}^N \mathbf{u}_{j \rightarrow i} \right)^S \left[1 + 0.15(Re_i)^{0.687} \right] \right\}$$



Akiki, Jackson, Balachandar, JFM, 813, 882-928 (2017)
Akiki, Moore, Balachandar, JCP, 351, 329-357 (2017)

CCMT | 7

Data-Driven Volume Fraction Correction

$$R^2 = 1 - \frac{\sum_{n=1}^{N_p} [F_{DNS}(n) - F_{PI}(n)]^2}{\sum_{n=1}^{N_p} [F_{DNS}(n) - \langle F_{DNS} \rangle]^2}$$

Case	Lateral Force R ² (DNS vs PIEP)
$\phi = 0.1, Re = 40$	0.68
$\phi = 0.2, Re = 16$	0.34
$\phi = 0.45, Re = 21$	0.09

$$\mathbf{F}_{PIEP,Data-Driven} = \mathbf{F}_{PIEP} + \mathbf{F}_{\phi,C}$$

$$\mathbf{T}_{PIEP,Data-Driven} = \mathbf{T}_{PIEP} + \mathbf{T}_{\phi,C}$$

where

$$\mathbf{F}_{\phi,C} \equiv \mathbf{F}_{\phi,C}(Re, \phi, r_1, r_2, \dots, r_N)$$

$$\mathbf{T}_{\phi,C} \equiv \mathbf{T}_{\phi,C}(Re, \phi, r_1, r_2, \dots, r_N)$$

CCMT | 8

UF UNIVERSITY OF FLORIDA **Nonlinear Regression Modeling**

For a given Re and volume fraction:

Response Variable (output)

$F_{\phi,C} \equiv \text{function of } \{\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_N\}$
 $T_{\phi,C} \equiv \text{function of } \{\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_N\}$

Predictor Variables (inputs)

Function Form and Parameters

Let us define a set of scalar invariants (I) that fully define the configuration formed by the N neighbors.

x – Separation : $r_{x,1}, r_{x,2}, \dots, r_{x,N}$

y – Separation : $r_{y,1}, r_{y,2}, \dots, r_{y,N}$

z – Separation : $r_{z,1}, r_{z,2}, \dots, r_{z,N}$

CCMT 9

UF UNIVERSITY OF FLORIDA **Regression Modeling (drag)**

For a given Re and volume fraction:

Cost (error) evaluation and gradient decent

The diagram illustrates the regression modeling process. On the left, a 'Parameter array' contains β . Below it, 'Predictor Variables (inputs)' are listed as $r_1, r_2, r_3, \dots, r_N$. Each predictor variable r_i is fed into a corresponding function block $F(\beta, r_i)$. These function blocks are collectively labeled as the 'Postulated Functional Form'. The outputs of these functions are summed in a block labeled Σ to produce the 'Prediction' ($D_{\text{Prediction}}$). This prediction is compared against the 'Response Variable (output)' (D_{DNS} or $D_{\text{DNS}} - D_{\text{PREP}}$) to calculate the Mean Squared Error (E_{MSE}). The error is then used to determine the gradient $\partial E_{\text{MSE}} / \partial \beta_i$, which is fed back into the parameter array β for gradient descent.

CCMT 10

Postulating the Functional Form

$$D(I) = \sum_{i=1}^N \left[\left(\sum_{m=1}^M \sum_{l=0}^L a_{l,m} j_l(k_{j,l,m} r_i) Y_{l,0}(\theta_i) + \sum_{m=1}^M \sum_{l=0}^L b_{l,m} n_l(k_{n,l,m} r_i) Y_{l,0}(\theta_i) \right) H(r_i) \right]$$

$$L_y(I) = \sum_{i=1}^N \left[\left(\sum_{m=1}^M \sum_{l=0}^L a_{l,m} j_l(k_{j,l,m} r_i) Y_{l,0}(\theta_i) + \sum_{m=1}^M \sum_{l=0}^L b_{l,m} n_l(k_{n,l,m} r_i) Y_{l,0}(\theta_i) \right) \hat{\mathbf{r}}_i \cdot \mathbf{e}_y H(r_i) \right]$$

$$T_z(I) = \sum_{i=1}^N \left[\left(\sum_{m=1}^M \sum_{l=0}^L a_{l,m} j_l(k_{j,l,m} r_i) Y_{l,0}(\theta_i) + \sum_{m=1}^M \sum_{l=0}^L b_{l,m} n_l(k_{n,l,m} r_i) Y_{l,0}(\theta_i) \right) \hat{\mathbf{r}}_i \cdot \mathbf{e}_y H(r_i) \right]$$

where

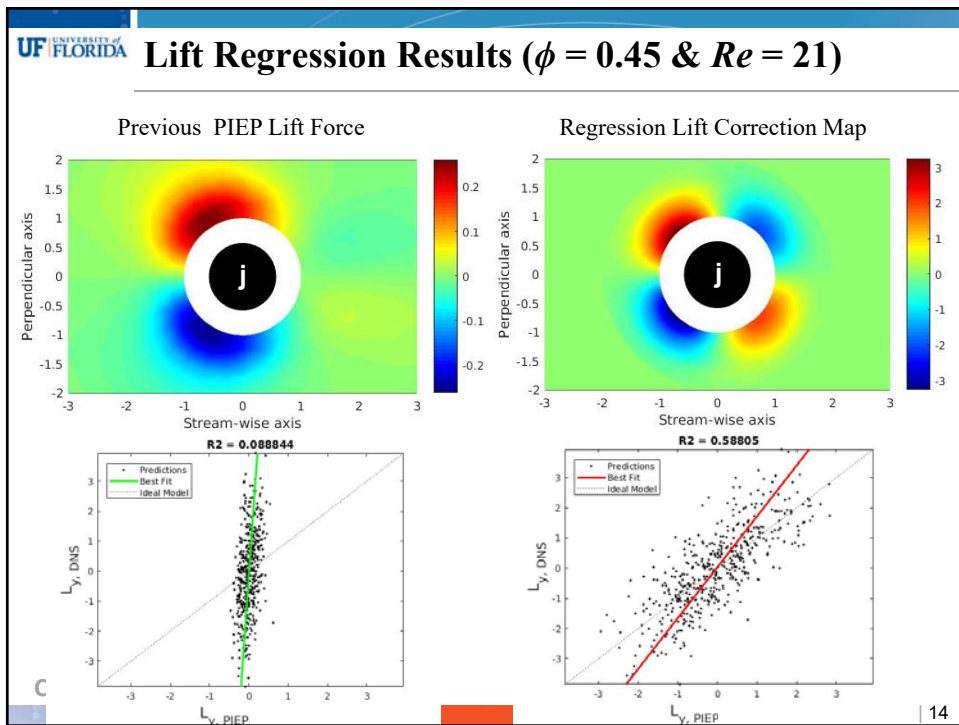
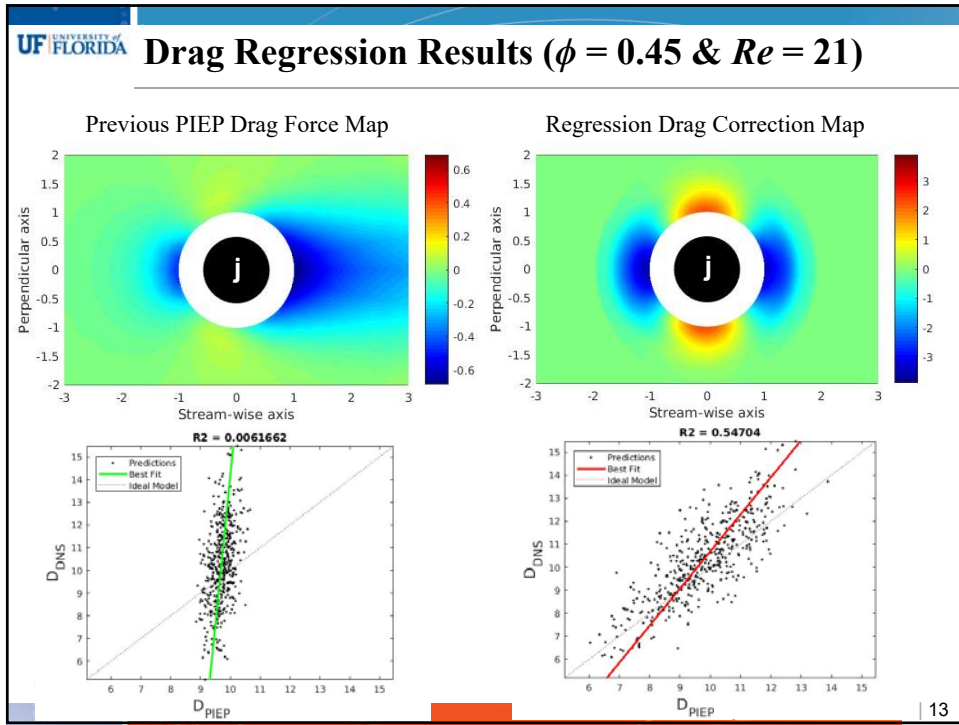
$$Y_{l,0}(\theta) = \sqrt{\frac{2l+1}{4\pi}} P_l(\cos \theta) \quad \frac{dj_l(k_{j,l,m} r_{min})}{dr} = 0 \quad \text{and} \quad \frac{dn_l(k_{n,l,m} r_{min})}{dr} = 0.$$

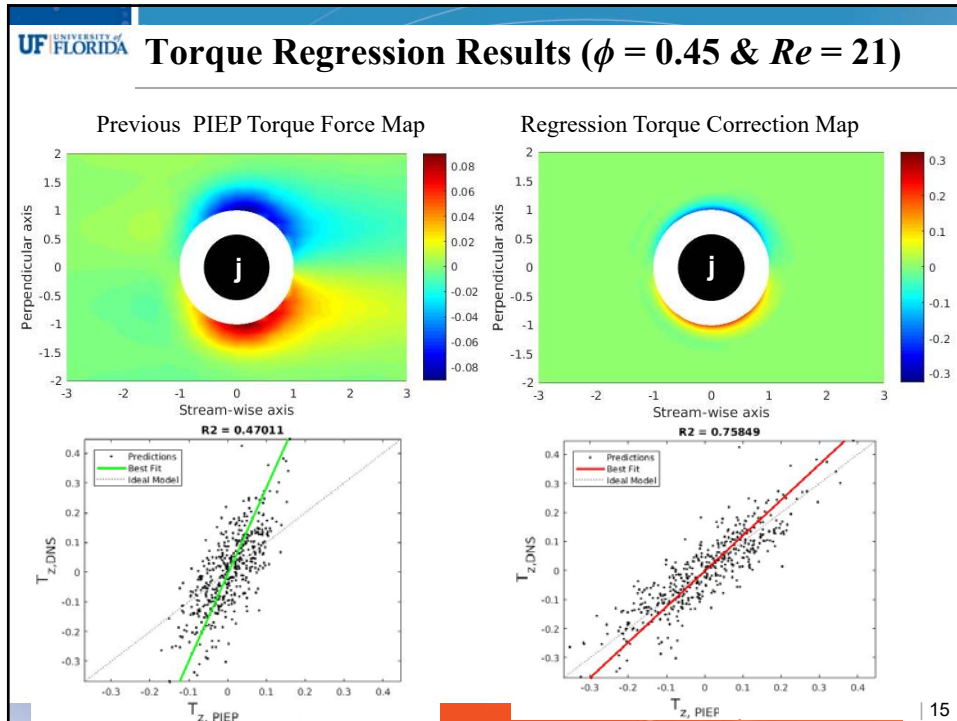
$a_{l,m}$ and $b_{l,m}$ make up the array of parameters, β , to be determined by regression
 N , M , and L are the hyper parameters that must be optimized using a second data set

Coefficient of Determination (R^2) Results

R^2 Values:		Current PIEP Model			Data-Driven		
ϕ	Re	Drag	Lift	Torque	Drag	Lift	Torque
0.1	40	0.70	0.68	0.75	0.72	0.75	0.79
0.1	70	0.65	0.68	0.65	0.67	0.72	0.72
0.1	173	0.35	0.59	0.45	0.44	0.60	0.58
0.2	16	0.38	0.34	0.48	0.66	0.74	0.71
0.2	89	0.50	0.48	0.72	0.62	0.63	0.77
0.45	21	0.01	0.09	0.47	0.55	0.59	0.76
0.45	115	0.21	0.19	0.51	0.63	0.57	0.65

$$R^2 = 1 - \frac{\sum_{n=1}^{N_p} [F_{DNS}(n) - F_{PI}(n)]^2}{\sum_{n=1}^{N_p} [F_{DNS}(n) - \langle F_{DNS} \rangle]^2}$$





UNIVERSITY OF FLORIDA **Main Message**

- Neighboring particle locations matter
 - Local volume fractions is not sufficient for force modeling
- Fluid-mediated Particle-Particle interactions are strong
- Previously formulated PIEP model provides accurate forces/torque predictions at low volume fractions
- Implementing a data driven approach allows the PIEP model to predict forces/torques at high volume fractions


CCMT

16

CCMT

Thank you! Questions?

Acknowledgment:
This material is based upon work supported in part by National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1315138 and in part by the the U.S. Department of Energy, National Nuclear Security Administration, Advanced Simulation and Computing Program, as a Cooperative Agreement under the Predictive Science Academic Alliance Program, under Contract No. DE-NA0002378.



17

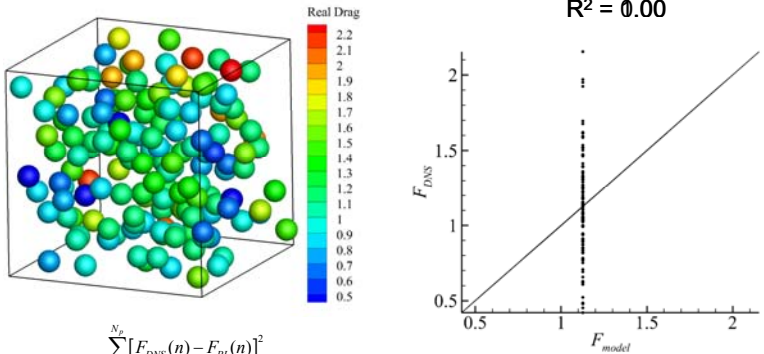
UF UNIVERSITY of FLORIDA

Extra Slides:

CCMT

18

UF UNIVERSITY OF FLORIDA **Ideal Point Particle Model**



$$R^2 = 1 - \frac{\sum_{n=1}^{N_p} [F_{DNS}(n) - F_P(n)]^2}{\sum_{n=1}^{N_p} [F_{DNS}(n) - \langle F_{DNS} \rangle]^2}$$

$R^2 = 0.00$

If the model is EXACT

Recovers Fully-Resolved physics

CCMT | 19

UF UNIVERSITY OF FLORIDA **Postulating the Functional Form**

Substitute a general functions for neighbor specific functions ($F_{x,i}$, F_i , and T_i),

$$\mathbf{F}_{VF} = \sum_{i=1}^N (F_{x,P}(I_i) \mathbf{e}_x + F_P(I_i) \hat{\mathbf{r}}_i) \quad \mathbf{T}_{VF} = \sum_{i=1}^N (T_P(I_i) \mathbf{e}_x \times \hat{\mathbf{r}}_i)$$

Individual component functions:

$$\mathbf{F}_{VF} = D(I) \mathbf{e}_x + L_y(I) \mathbf{e}_y + L_z(I) \mathbf{e}_z \quad \mathbf{T}_{VF} = T_x(I) \mathbf{e}_x + T_y(I) \mathbf{e}_y + T_z(I) \mathbf{e}_z$$

Combine the above formulations:

$$D(I) = \sum_{i=1}^N (F_{x,P}(I_i) + F_P(I_i) \hat{\mathbf{r}}_i \cdot \mathbf{e}_x), \quad T_x(I) = 0,$$

$$L_y(I) = \sum_{i=1}^N (F_P(I_i) \hat{\mathbf{r}}_i \cdot \mathbf{e}_y), \quad T_y(I) = \sum_{i=1}^N (T_P(I_i) \hat{\mathbf{r}}_i \cdot \mathbf{e}_z),$$

$$L_z(I) = \sum_{i=1}^N (F_P(I_i) \hat{\mathbf{r}}_i \cdot \mathbf{e}_z), \quad T_z(I) = \sum_{i=1}^N (T_P(I_i) \hat{\mathbf{r}}_i \cdot \mathbf{e}_y).$$

CCMT | 20

UF UNIVERSITY OF FLORIDA **Postulating the Functional Form**

The function is only defined within radius of influence (r_{max})

$$H(r) = \begin{cases} 0 & r < d \\ 1 & d \leq r \leq r_{max} \\ 0 & r > r_{max} \end{cases}$$

where r_{max} can be found by root finding the following:

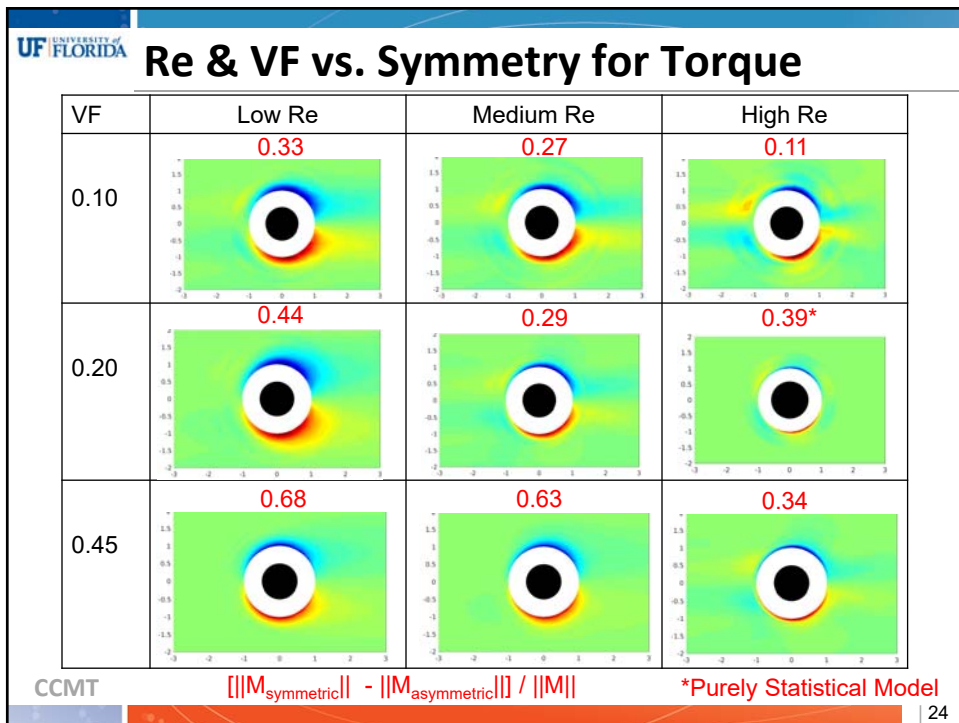
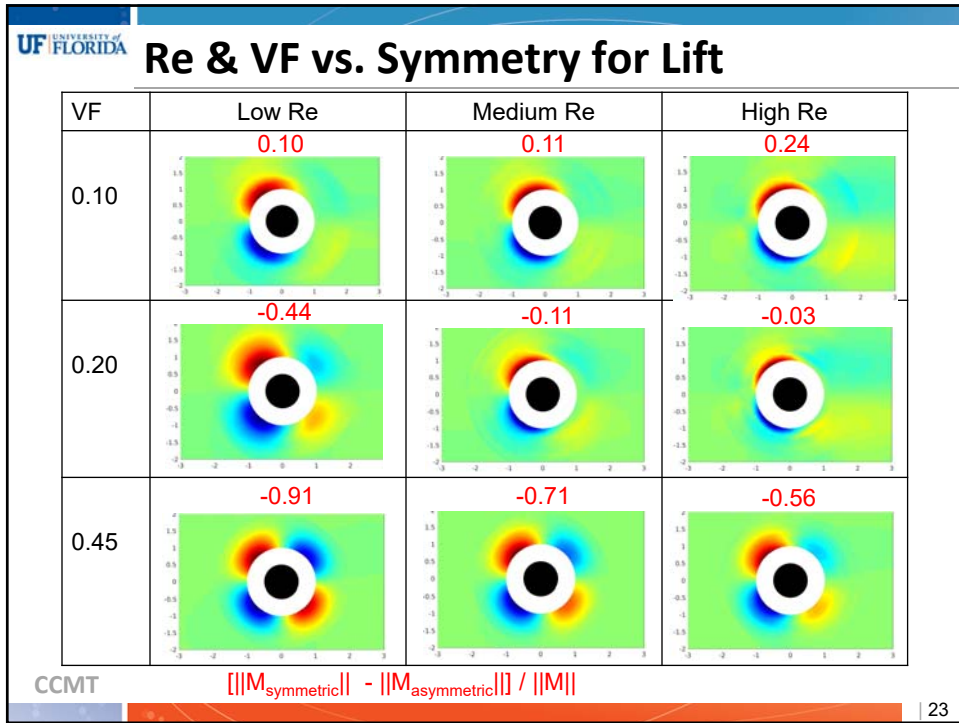
$$\int_{V_d}^{V_{r_{max}}} g(r) \rho dV - N_{train} = 0$$

CCMT | 21

UF UNIVERSITY OF FLORIDA **Re & VF vs. Symmetry for Drag**

VF	Low Re	Medium Re	High Re
0.10	0.34	0.38	0.43
0.20	0.63	0.58	0.57
0.45	0.91	0.90	0.85

CCMT $\frac{||M_{symmetric}|| - ||M_{asymmetric}||}{||M||}$ | 22



CCMT

Microscale Shock and Contact Simulations

Brandon Osborne



UF UNIVERSITY OF FLORIDA

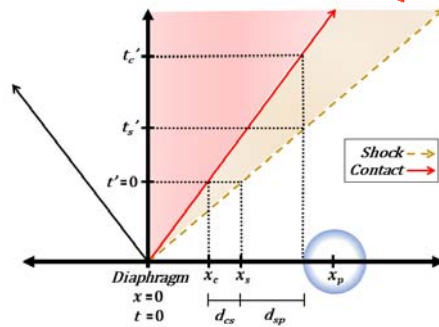
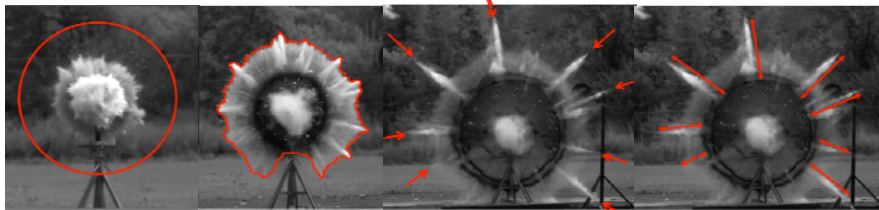
Motivation

PM-1: Blast Wave Location

PM-2: Particle Front Location

PM-3: Number of Instability Waves

PM-4: Amplitude of Instability Waves



CCMT

2

Simulation Overview

- Three sets simulations:
 - Close: Shock and contact reach first particle nearly simultaneously
 - Intermediate: Shock is 2 particle diameters downstream of first particle before the contact reaches its leading edge
 - Shock only: The simulation is absent a contact discontinuity

ϕ	M_{ct}	M_s	ρ_1 (kg/m ³)	ρ_2 (kg/m ³)	ρ_3 (kg/m ³)	ρ_2/ρ_1	ρ_3/ρ_1
5-40%	0.31	1.22	1.20	1.65	2.15	1.37	1.78
	0.90	1.90	1.20	3.03	8.20	2.52	6.81
	1.26	2.69	1.20	4.27	26.35	3.54	21.87

CCMT 3

Contours: $\phi = 10\%$, $M_{ct} = 0.31$, Close

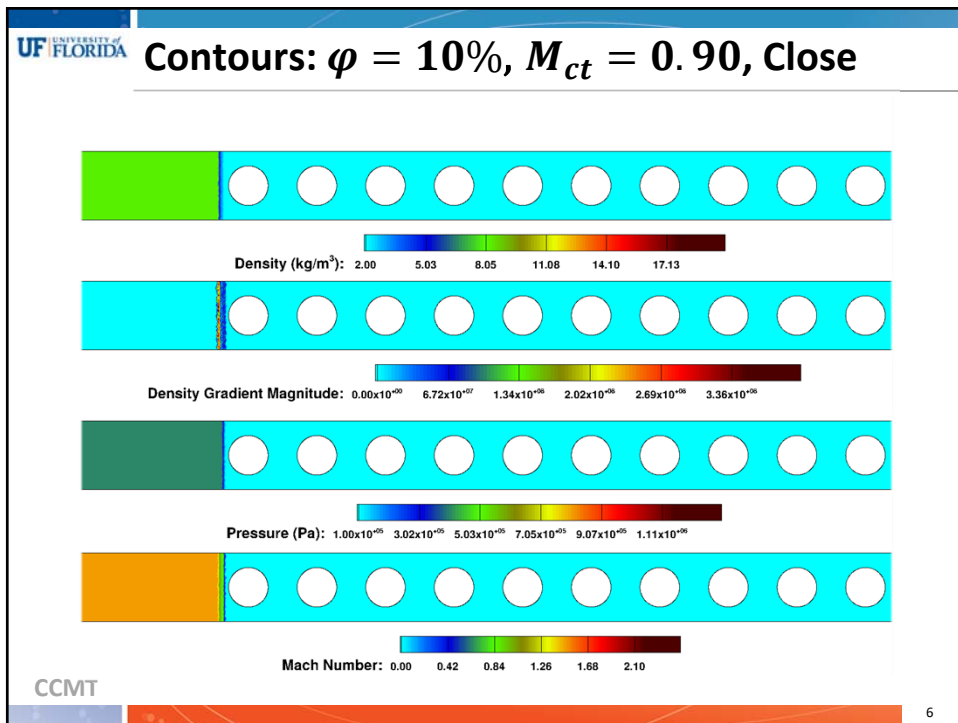
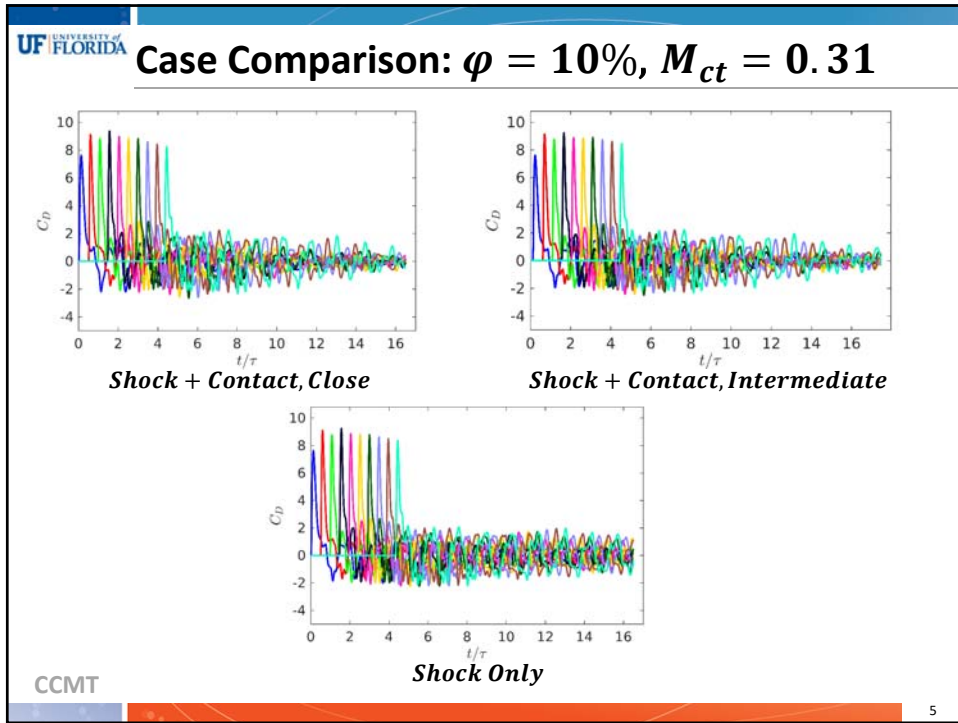
Density (kg/m³): 1.30 1.47 1.65 1.82 1.99 2.16 2.34

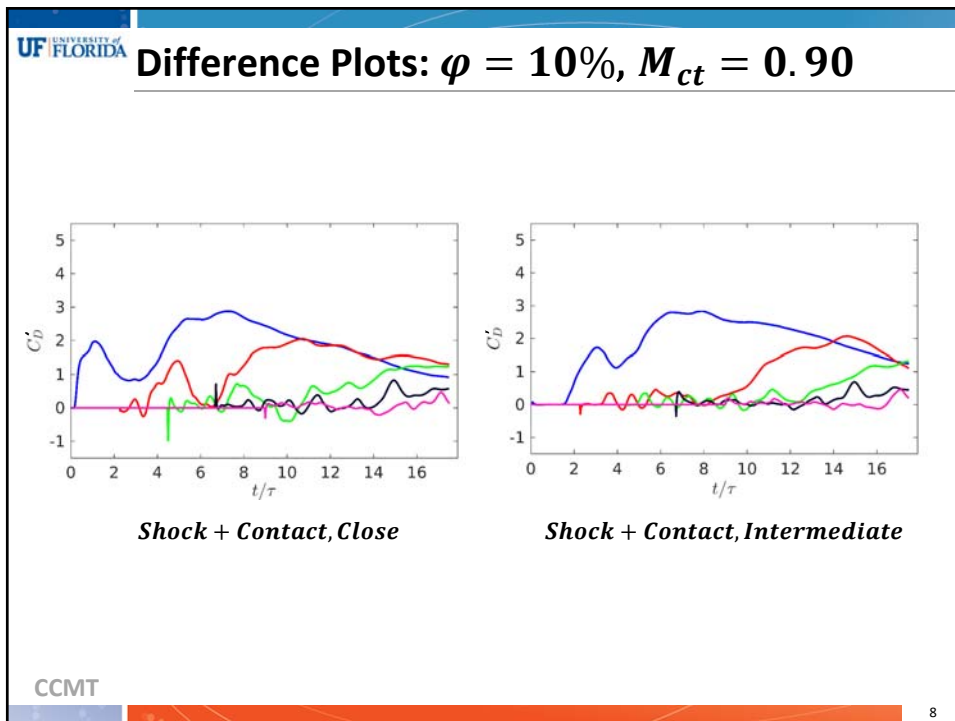
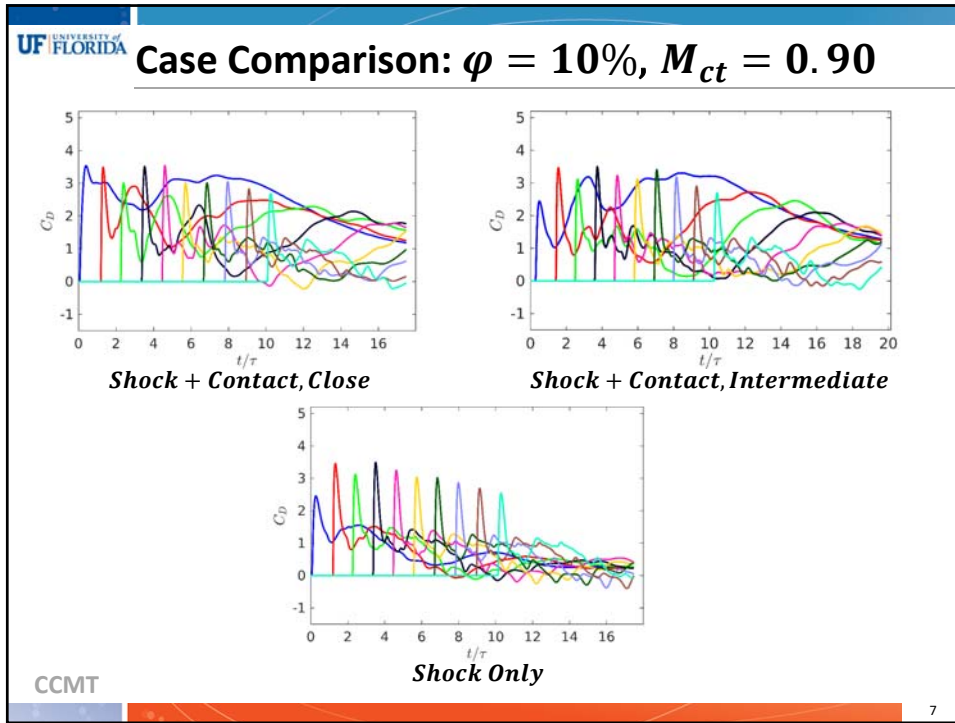
Density Gradient Magnitude: 1.00×10^{-05} 4.67×10^{-06} 9.33×10^{-06} 1.40×10^{-05} 1.87×10^{-05}

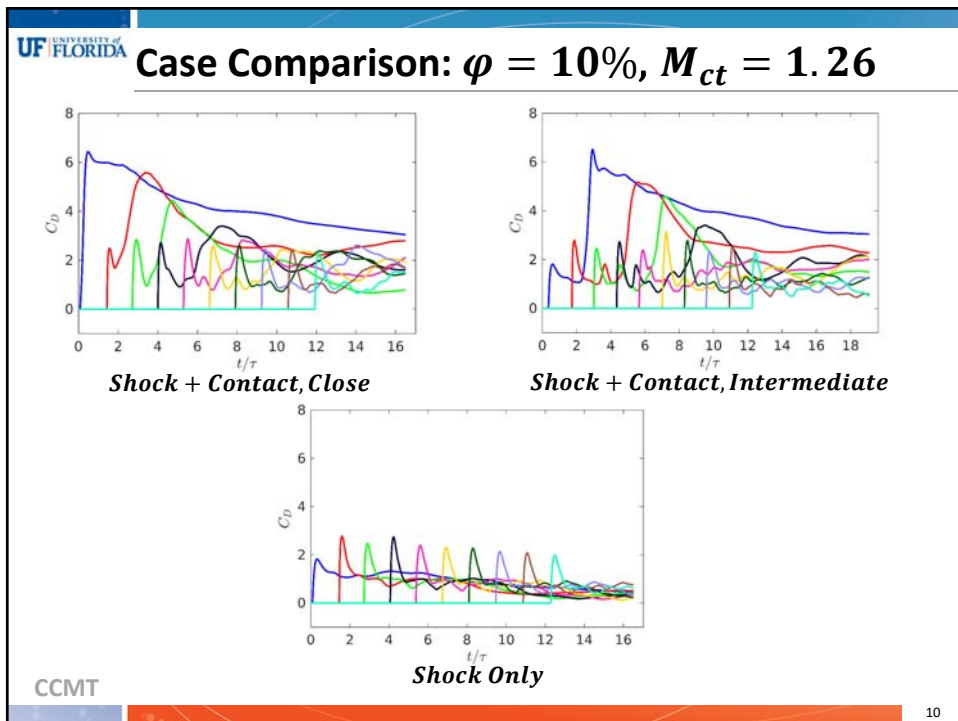
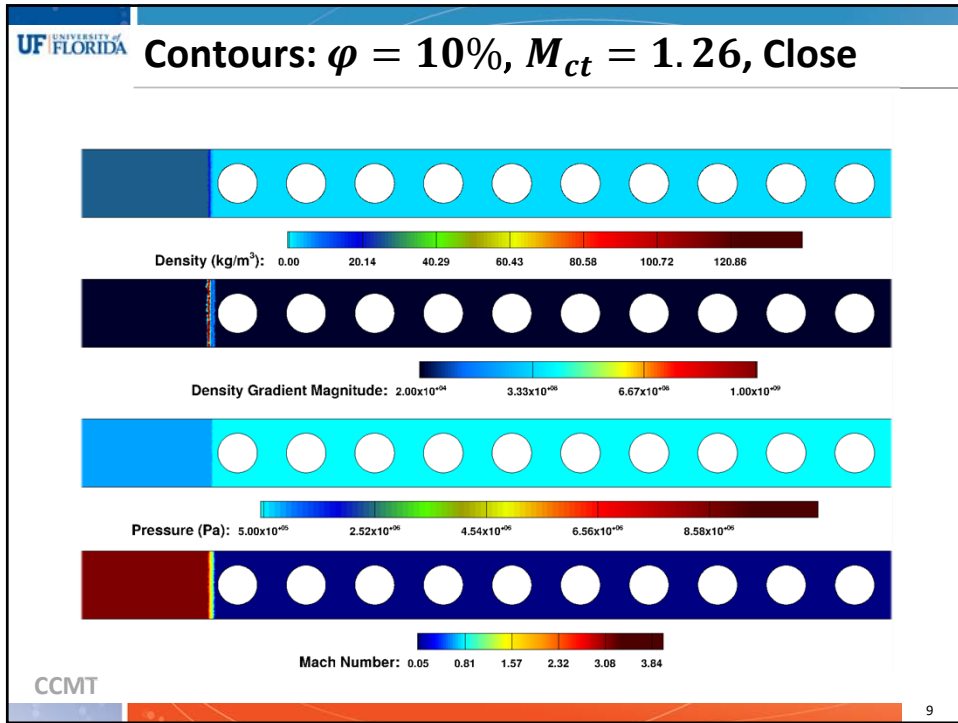
Pressure (Pa): 1.10×10^{-06} 1.25×10^{-06} 1.40×10^{-06} 1.55×10^{-06} 1.71×10^{-06} 1.86×10^{-06}

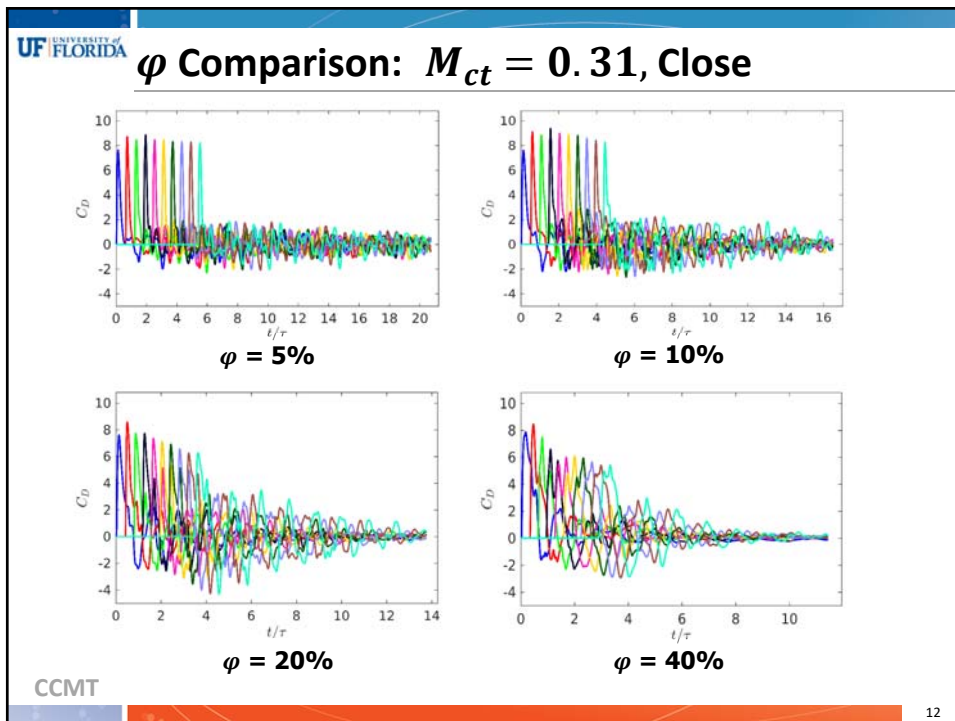
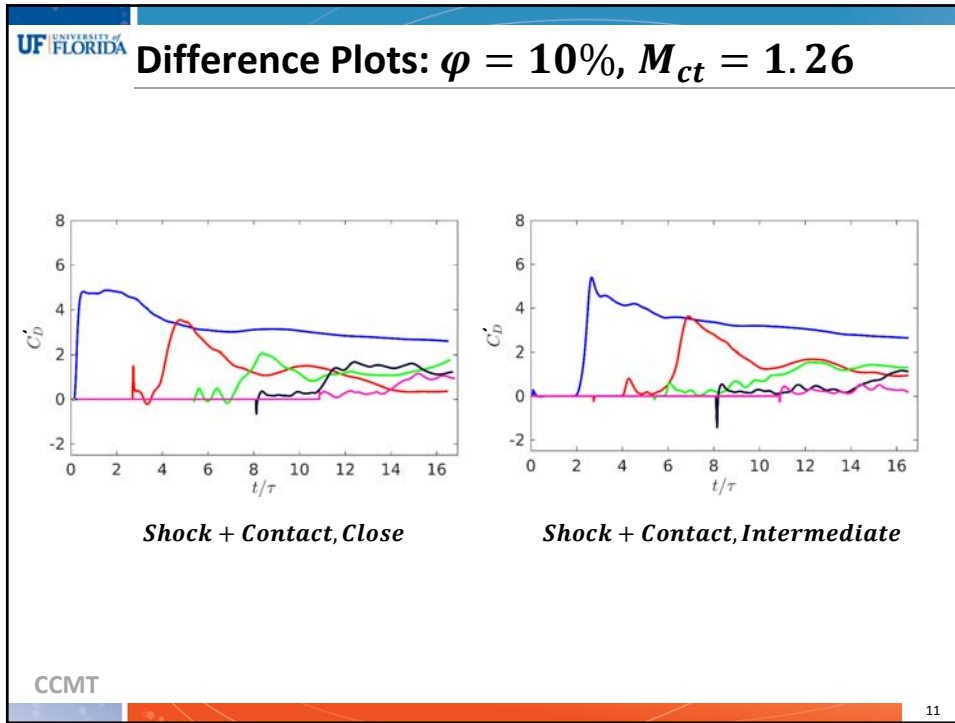
Mach Number: 0.05 0.14 0.23 0.33 0.42 0.51

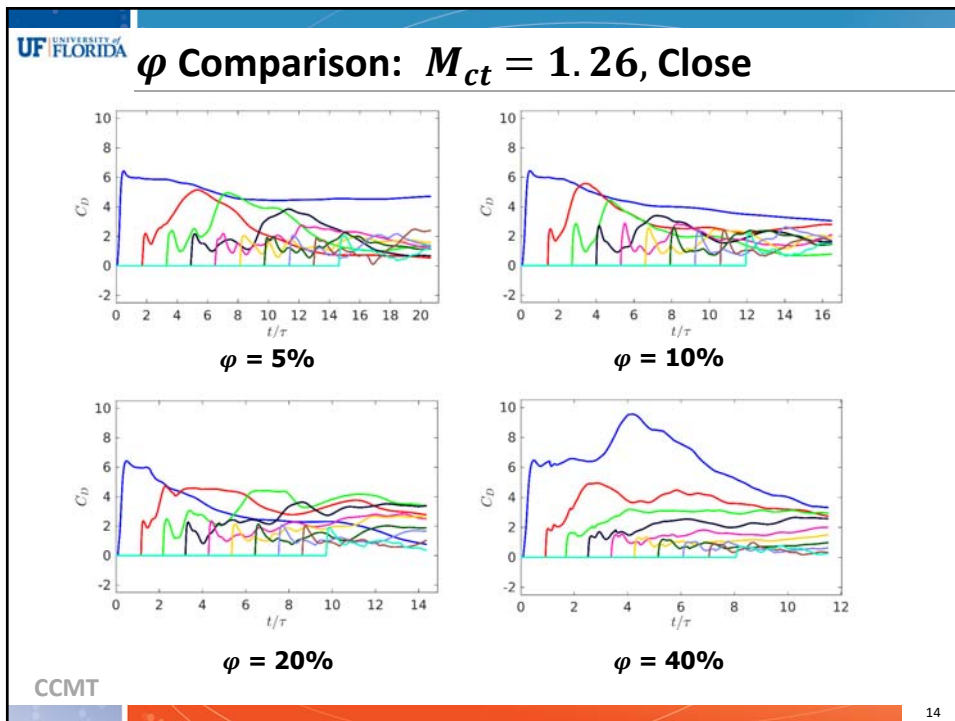
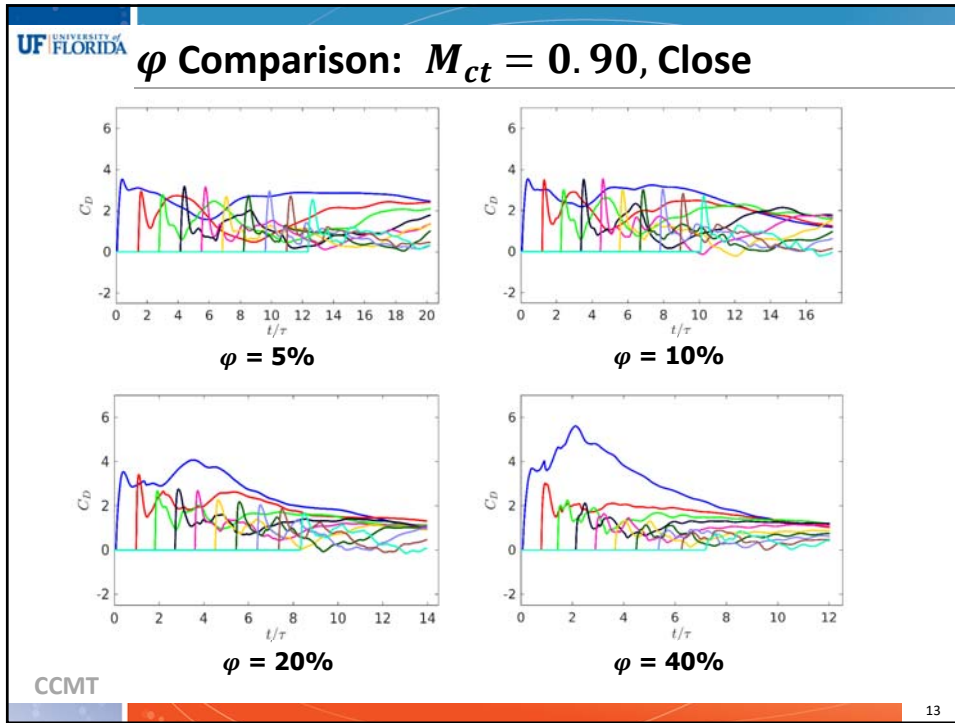
CCMT 4









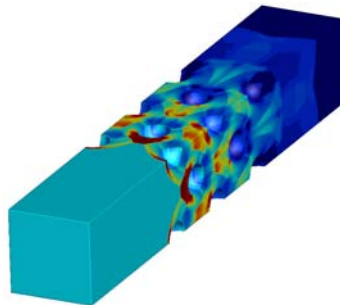


Summary

- Subsonic post-shock Mach number
 - Formation of a wake as the contact passes the particles that results in a “stretching” of the contact interface
 - Force oscillations created by reflected waves are dampened by the contact
 - Oscillations of greater magnitude as volume fraction increases and a decrease in peak force for subsequent particles for higher volume fractions
- Near sonic post-shock Mach number
 - Rapid mixing of the contact interface
 - Formation of compression waves traveling upstream and shocks extending from particle surface to wall after sonic flow is reached
 - Increasing force on the first particle and decreasing force on subsequent particles as volume fraction increases
- Supersonic post-shock Mach number
 - Rapid mixing of the contact interface
 - Formation of bow shocks and shocklets
 - High particle forces and the formation of a compression wave traveling upstream for $\varphi = 40\%$

Future Work

- Shock and contact interaction with an FCC array of particles
 - Characterize the effects a shock and contact have on force history and flow field compare to current 1D array data
- Shock and contact interaction with a random arrangement of particles
 - Apply techniques and models developed from 1D and FCC arrays to a random arrangement of particles
- PIEP model application to shock-contact-particle interaction



CCMT

Thank you!
Do you have any
questions?



CCMT

BE Simulations of CMT-nek

Sai Chenna (BE)



The slide features a blue vertical bar on the left with the text 'CCMT'. The main content is centered on a white background. At the bottom, there is an orange horizontal bar containing the logos for the University of Florida, the Florida Department of Energy & Environment, and NASA.

UF UNIVERSITY OF FLORIDA

Outline: BE-simulation of CMT-nek

- Particle-solver
- Modelling approach
- Particle-distribution tool
- DSE of CMT-nek using BE

CCMT

2

CMT-nek DSE: Motivation & Approach

- Motivation
 - CMT-nek has huge design space
 - Various architectural options exist for Exascale systems
- Goal
 - Use BE methods & tools to perform DSE
 - Approach
 - Perform BE Simulations of CMT-nek (baseline)
 - Identify optimization candidates (i.e. most expensive subroutines)
 - Create and validate models of algorithms for these subroutines
 - Use BE to predict performance

CCMT
3

CMT-nek: Particle Solver subroutine

- Particle solver – expensive kernel in CMT-nek
 - Calculates the particle properties at each time-step
 - Assumptions
 - No particle to particle interaction
 - No two-way coupling
 - Parameters
 - N – element size
 - $nelt$ – elements-per-processor
 - α – particles/gridpoint
 - N_p - # particles = $\alpha * N^3 * nelt$

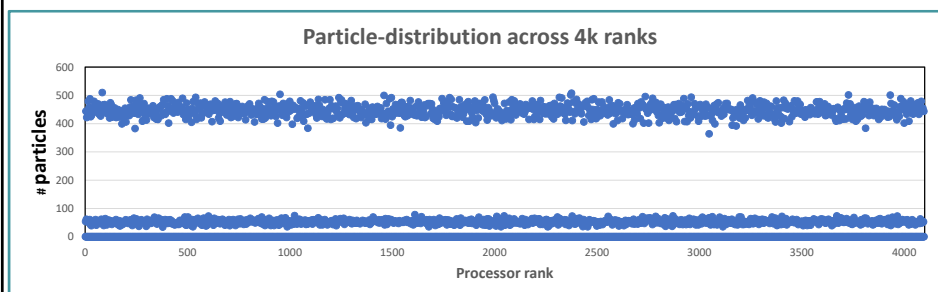
CCMT
4

Modelling Approach

- Symbolic Regression
 - Tool to generate multi-parameter performance models for computation kernels
 - No prior knowledge of kernel required
 - Captures machine-specific performance behaviours
- Trace-driven simulation
 - Building a tool which determines particle distribution from a trace file based on user-specified parameters
 - Determines # particles residing and moving in each processor at given time-step
 - Improves accuracy of BE-simulation

Modelling Approach: Trace-driven simulation

- Particle solver kernel
 - Workload per processor depends on # particles
 - # particles/processor is dynamic
 - varies among processors – *depends on total # of processors*
 - varies at each timestep – *based on fluid forces on particles*
 - Need a trace to perform simulations



Modelling Approach: Trace-driven simulation

- Particle-distribution tool
 - Input: trace data containing particle location at each time-step
 - Output
 - # particles residing in each rank @ every timestep
 - # particles moving across each rank @ every timestep
 - Particle movement doesn't depend on # processors
 - Single trace for a given problem size is sufficient to predict particle movement for any # of processors

0	1
2	3

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

CCMT 7

Particle-distribution tool: Results

Element size – 11, # of elements – 262144, # particles - 512000

Particle-distribution across 4k ranks

Particle-distribution across 32k ranks

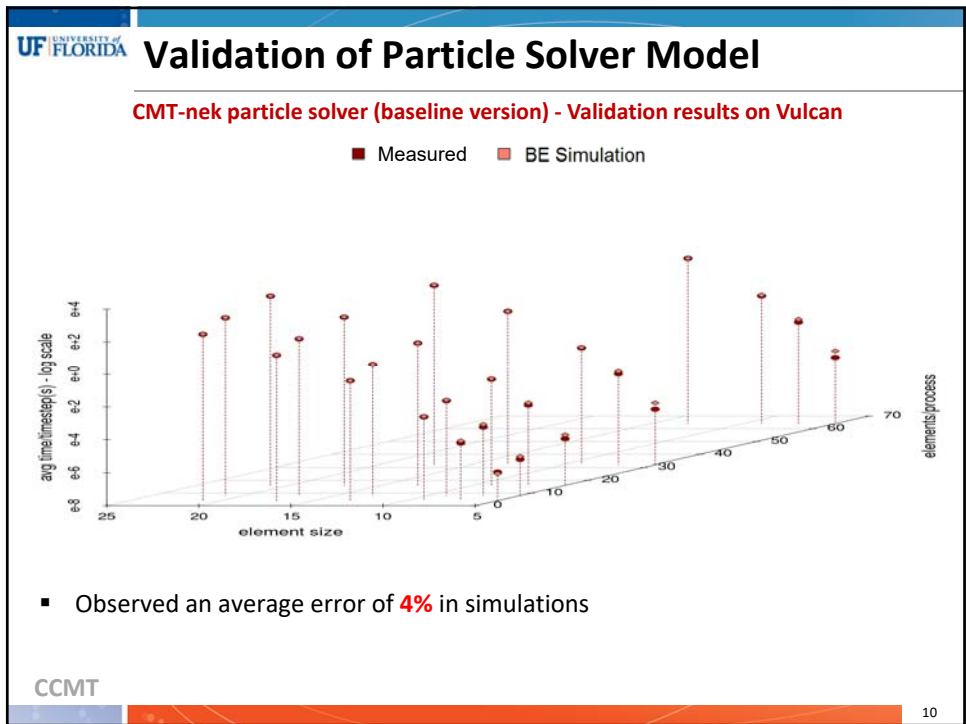
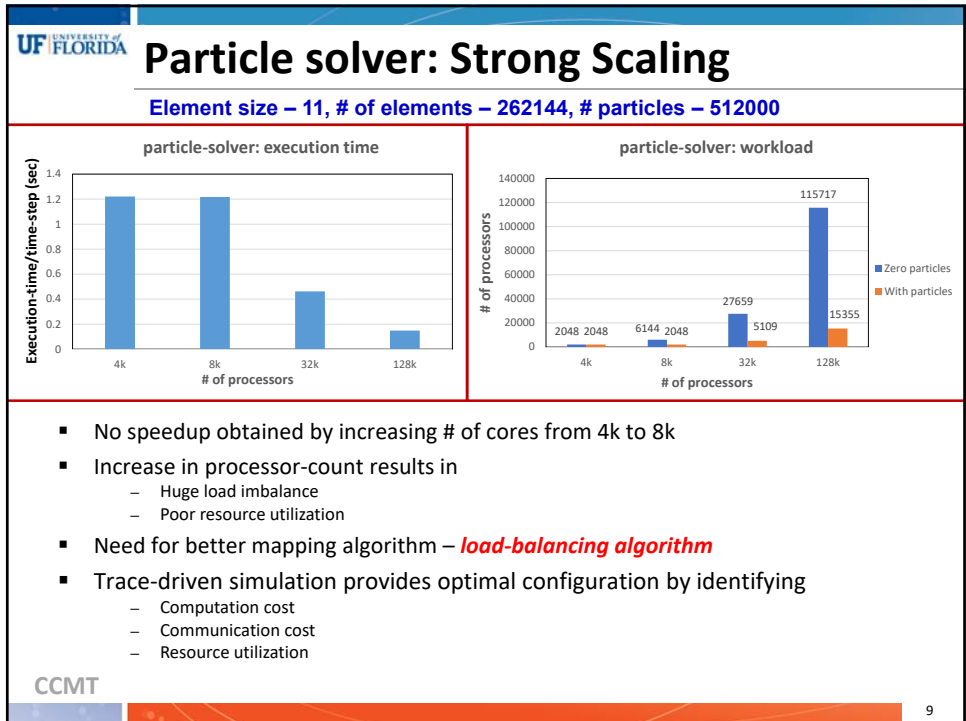
Particle-distribution across 128k ranks

particle-solver execution time across 4k ranks

particle-solver execution time across 32k ranks

particle-solver execution time across 128k ranks

CCMT 8



Particle Solver: Algorithmic options

- Evaluate performance of various algorithmic options available for particle-solver kernel
- Time Integration** - solve differential equations to calculate particle properties
 - Current : **Runge-Kutta 3 (rk3)** – 3 stage time integration
 - Alternate : **Backward Differentiation Formula (bdf)** – single stage time integration
- Particle Interpolation** - interpolates fluid properties acting on particles
 - Current : **Barycentric Interpolation**
 - Alternate : **reduced Barycentric Interpolation, Tri-linear Interpolation**

Control-flow graph of rk3 algorithm

Control-flow graph of bdf algorithm

CCMT 11

Simulator Predictions: Time Integration

Simulation predictions on Vulcan

64 elements/processor
0.1 particle/gridpoint

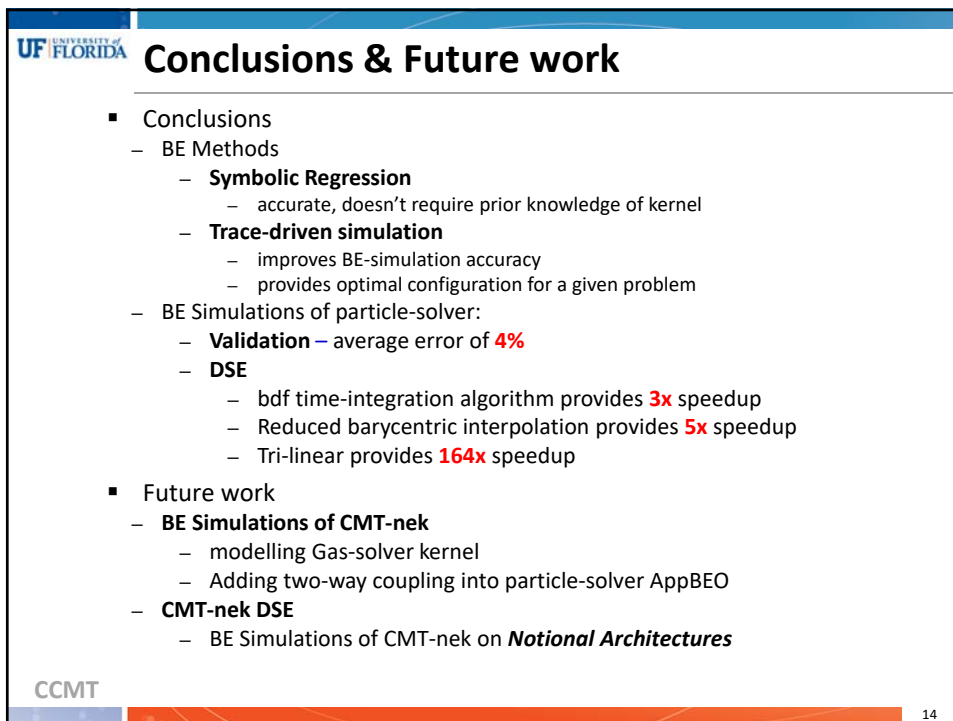
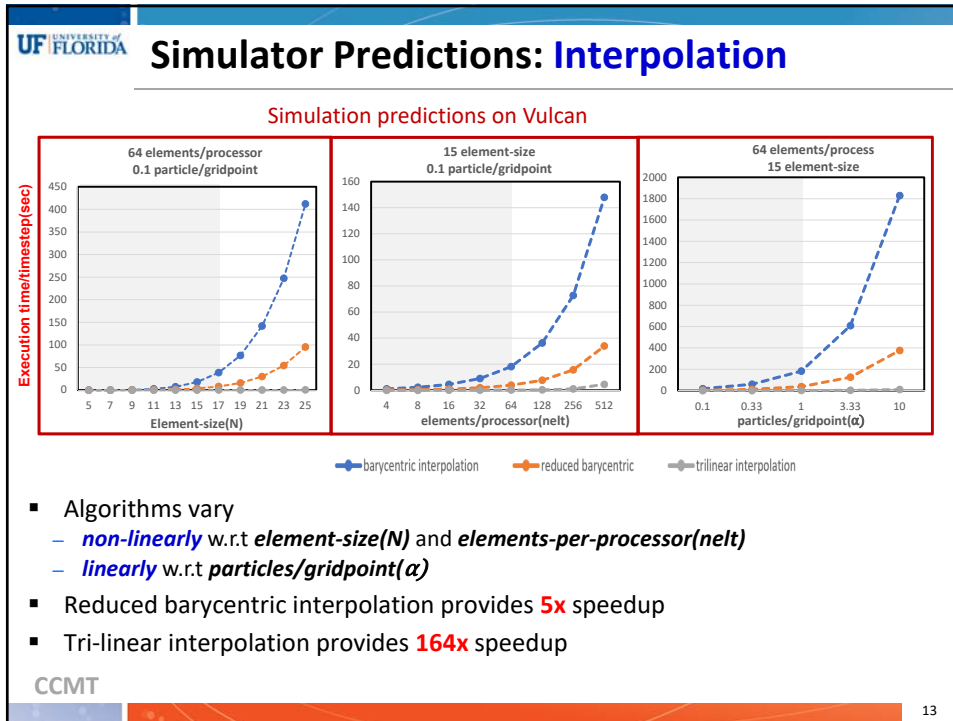
15 element-size
0.1 particle/gridpoint

64 elements/process
15 element-size

● rk3 integration ● bdf integration

- Both algorithms vary
 - non-linearly* w.r.t *element-size(N)* and *elements-per-processor(nelt)*
 - linearly* w.r.t *particles/gridpoint(alpha)*
- bdf time integration provides **3x** speedup over rk3

CCMT 12



CCMT

***Do you have any
questions?***

UF UNIVERSITY of
FLORIDA



NNSA