

Computational Models for Polydisperse Particulate and Multiphase Systems

Rodney O. Fox International Francqui Professor

# Computational Models for Polydisperse Particulate and Multiphase Systems

### Rodney O. Fox International Francqui Professor

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## Lecture Topics

Computational Models for Polydisperse Particulate and Multiphase Systems

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- 1 Introduction to Disperse Multiphase Flows
- 2 Mesoscale Description of Polydisperse Flows
- 3 Quadrature-Based Moment Methods
- Generalized Population Balance Equation
- **6** Mesoscale Models for Physical and Chemical Processes
- 6 Solution Methods for Homogeneous Systems

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## Lecture Topics

Computational Models for Polydisperse Particulate and Multiphase Systems

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8 High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

- **9** Application to Fine-Particle Formation
- Application to Bubbly Flows
- Application to Gas–Particle Flows
- Turbulence Modeling for Disperse Multiphase Flows



## Part 1

Computational Models for Polydisperse Particulate and Multiphase Systems

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Introduction to Disperse Multiphase Flows

Definition and Examples

Simulation Methods Number Density

Functions Different Types of

Mesoscale Description of Polydisperse Flows

Population Balance Equation

Generalized Population Balance Equation

Simple Example

# INTRODUCTION TO DISPERSE MULTIPHASE FLOWS

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Computational Models for Polydisperse Particulate and Multiphase Systems

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#### Introduction to Disperse Multiphase Flows

- Definition and Examples
- Simulation Methods Number Density Functions
- Different Types of NDF
- Mesoscale Description of Polydisperse Flows
- Population Balance Equation
- Generalized Population Balance Equation
- Simple Example

- Systems we consider are constituted by multiple phases of which one phase is continuous
- Others are **dispersed**, namely composed of discrete elements
- Discrete elements can be solid particles, droplets or bubbles
- Relevant properties of disperse phase(s), such as mass, momentum, or energy, change from element to element, generating distributions or number density functions
- Typical examples are crystal size distribution (CSD), particle size distribution (PSD), and particle velocity distribution (PVD)
- Elements of disperse phase(s) continuously evolve due to phase coupling (one-, two-, three- and four-way coupling)



## Examples

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## **Overview of Different Simulation Methods**

Fully resolved

Lagrangian

point-particle

Fulerian

Equilibrium

Èulerian

Dusty

das

10-6

Dilute suspension

one- or two-way coupled

10-3

Dense suspension

four-way coupled

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DNS:  $(d/\eta)$  or LES:  $(d/\xi)$ **DNS:**  $(\tau_p/\tau_k)$  or LES:  $(\tau_p/\tau_\xi)$ 

10-

#### Introduction to Disperse Multiphase Flows

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- Fully resolved approach (e.g. Discrete element method): see for example work of Subramaniam group at ISU
- Lagrangian point-particle approach: see for example work of Soldati group at the Univ. of Udine (Italy)
- Eulerian approach: disperse phase is treated as a continuum through concept of number density function



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- Problem of describing evolution (in space and time) of these systems in Eulerian framework (in terms of number density functions or distributions) has been treated in many ways by different scientific communities
- Crystallization and precipitation (often neglecting spatial inhomogeneities): crystal or particle size, population balance equation (PBE)
- Evaporating (and non-evaporating) sprays: droplet surface area, **Williams–Boltzmann equation (WBE)**
- Aerosols and ultra-fine particles: particle mass, **particle** dynamics equation (PDE)
- Particulate systems involved in granular flows: particle velocity, **Boltzmann equation (BE)**
- Although these apparently different theoretical frameworks are referred to by different names, underlying theory (which has its foundation in classical statistical mechanics) is exactly the same!



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## Microscale versus Mesoscale

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Generalized Population Balance Equation Simple Example • Microscale description resolves all details:

Fluid velocity: Navier–Stokes eq. no-slip BC on particle surface

$$M_p^{(n)} \frac{d^2 \mathbf{X}^{(n)}}{dt^2}$$
 = Fluid force + collisions

Very fine grid needed to predict forces



• Mesoscale description works with distributions:

Fluid velocity: Navier–Stokes eq. with coupling terms Population balance equation for distribution





## Microscale versus Mesoscale

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Particle



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### A plethora of methods have been generated:

- In PBE, distribution is often discretized into classes (sections), generating discretized population balance equation (DPBE)
- Among many methods developed, one used in computational fluid dynamics (CFD) is multiple-size-group (MUSIG) method
- Same discretization is carried out for BE in discrete velocity method (DVM) and lattice Boltzmann method (LBM)
- Method of moments (MOM) is used for solution of both PBE and BE, but resulting closure problem is overcome by following different strategies (e.g. Grad method, particle number density method, method of moments with interpolative closure – MOMIC, etc.)



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Simple Example

• Disperse phase is constituted by discrete elements

• Length scales of elements are smaller than length scale of spatial variation of properties of interest

• Each element has properties known as **coordinates** (i.e. two elements are identical if they have identical values for their coordinates)

• Coordinates are classified as **external (spatial coordinates)** and **internal** (properties such as mass, momentum, enthalpy, temperature, volume, surface area, size, or age)

• State of multiphase system is defined through number density function (NDF):  $n_{\xi}(t, \mathbf{x}, \xi)$  where  $\mathbf{x} = (x_1, x_2, x_3)$  and  $\xi = (\xi_1, \dots, \xi_M)$ 



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Simple Example

- NDF is expected number of entities in infinitesimal physical volume dx and in infinitesimal phase-space volume dξ: n<sub>ξ</sub> dx dξ
- NDF is not a random quantity, rather it is ensemble average of infinite realizations (corresponding to same identical macroscopic boundary and initial conditions) of multiphase system
- Being an average quantity, it is (usually) differentiable in space/time
- Underlying definition of NDF is a stochastic description (behavior of any single particle is regarded as random) but behavior of population of particles is treated as deterministic if number of particles in population is large!
- NDF identifies entire population of particles at any instant and at any given point in computational domain and considers probability associated with state of each of these particles



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- Number Density Functions
  - This random behavior may reflect some chaotic properties (e.g. Brownian motion) or some other behavior (e.g. microscale turbulence → NDF can be treated as any other scalar field)
  - Therefore n<sub>ξ</sub>(ξ) dξ represents number of disperse entities contained in phase-space volume dξ centered at ξ per unit of physical volume (i.e., number density)
  - Integration of NDF over all possible values of internal-coordinate vector:

$$N \equiv m_{\boldsymbol{\xi},0} \equiv \int_{\Omega_{\boldsymbol{\xi}}} n_{\boldsymbol{\xi}}(\boldsymbol{\xi}) \, \mathrm{d}\boldsymbol{\xi}$$

corresponding to zero-order moment of NDF

• Arbitrary integer moment of NDF is defined by

$$m_{\boldsymbol{\xi},\mathbf{k}} \equiv \int_{\Omega_{\boldsymbol{\xi}}} \boldsymbol{\xi}_1^{k_1} \cdots \boldsymbol{\xi}_M^{k_M} n_{\boldsymbol{\xi}}(\boldsymbol{\xi}) \, \mathrm{d}\boldsymbol{\xi}$$

where  $\mathbf{k} \equiv (k_1, \ldots, k_M)$ 



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Simple Example

- This random behavior may reflect some chaotic properties (e.g. Brownian motion) or some other behavior (e.g. microscale turbulence → NDF can be treated as any other scalar field)
- Therefore n<sub>ξ</sub>(ξ) dξ represents number of disperse entities contained in phase-space volume dξ centered at ξ per unit of physical volume (i.e., number density)
- Integration of NDF over all possible values of internal-coordinate vector:

$$N \equiv m_{\xi,0} \equiv \int_{\Omega_{\xi}} n_{\xi}(\xi) \,\mathrm{d}\xi$$

corresponding to zero-order moment of NDF

• Arbitrary integer moment of NDF is defined by

$$m_{\boldsymbol{\xi},\mathbf{k}} \equiv \int_{\Omega_{\boldsymbol{\xi}}} \boldsymbol{\xi}_1^{k_1} \cdots \boldsymbol{\xi}_M^{k_M} n_{\boldsymbol{\xi}}(\boldsymbol{\xi}) \, \mathrm{d}\boldsymbol{\xi}$$

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- Different definitions of univariate NDF are used in literature
- Choice is problem dependent (e.g. colloids, aerosols, droplets, etc.)
- A change of variables allows to go back and forth:

 $n_L(L) \, \mathrm{d}L = n_V(V) \, \mathrm{d}V = n_M(M) \, \mathrm{d}M$ 

so it suffices to know relation between length  $L\!\!,$  volume  $V\!\!$  and mass  $M\!\!$ 

• For example, if  $M = \rho V = \rho L^3$ :

$$n_M(M) = n_V(M/\rho) \frac{\mathrm{d}V}{\mathrm{d}M} = \frac{1}{\rho} n_V(M/\rho)$$

$$n_M(M) = n_L \left[ (M/\rho)^{1/3} \right] \frac{dL}{dM} = \frac{1}{3\rho} \left( \rho/M \right)^{2/3} n_L \left[ (M/\rho)^{1/3} \right]$$

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 $n_L(L) \, \mathrm{d}L = n_V(V) \, \mathrm{d}V = n_M(M) \, \mathrm{d}M$ 

so it suffices to know relation between length L, volume V and mass M

• For example, if  $M = \rho V = \rho L^3$ :

$$n_M(M) = n_V(M/\rho) \frac{\mathrm{d}V}{\mathrm{d}M} = \frac{1}{\rho} n_V(M/\rho)$$

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- Particles can be characterized by their size or length *L*
- Length-based NDF,  $n_L(t, \mathbf{x}, L)$ , is defined so that:  $n_L dL$  is expected number density of particles with length between *L* and L + dL
- Total number concentration can be calculated as:

$$N \equiv m_{\mathrm{L},0} = \int_0^\infty n_{\mathrm{L}}(L) \,\mathrm{d}L$$

· Number-averaged particle size can be defined as

$$L_{10} \equiv \frac{1}{N} \int_0^\infty L n_{\rm L}(L) \,\mathrm{d}L = \frac{m_{\rm L,1}}{N}$$

• We define *k*<sup>th</sup> moment of length-based NDF as

$$m_{\mathrm{L},k} \equiv \int_0^\infty L^k n_\mathrm{L}(L) \,\mathrm{d}L$$

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# Length-Based NDF

- Any mean particle size can be defined as ratio m<sub>L,k+1</sub>/m<sub>L,k</sub> for any value of k (k = 2, Sauter mean diameter, L<sub>32</sub> ≡ m<sub>L,3</sub>/m<sub>L,2</sub>)
- If volume scales with third power of length,  $V = k_V L^3$  (sphere:  $k_V = \pi/6$ , cube:  $k_V = 1$ , etc.), we can define *volume density function*  $V_L(L)$  representing volume of particles per unit spatial volume with lengths between *L* and L + dL:  $V_L \equiv k_V L^3 n_L$
- After normalizing  $V_{\rm L}$  to unity, volume-fraction density function  $\alpha_{\rm V}(L)$  represents volume fraction of particles with a specific length over total particle volume:  $\alpha_{\rm V}(L) := \frac{L^3 n_{\rm L}}{\int_{-\infty}^{\infty} L^3 m(L) dL}$
- Mean particle length calculated from volume-fraction density function is

$$L_{43} = \int_0^\infty \alpha_{\rm V}(L) L \, {\rm d}L = \frac{m_{\rm L,4}}{m_{\rm L,3}}$$



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#### Volume-Based NDF

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Simple Example

- Another common internal coordinate is particle volume V → volume-based NDF as expected number of particles with volume between V and V + dV: n<sub>V</sub> dx dV
- If volume and length scale with third power as  $V = k_V L^3$ , relationship between length-based and volume-based NDFs is straightforward:  $n_L(L) = 3k_V L^2 n_V (k_V L^3)$
- · Moments of volume-based number NDF are defined as

$$m_{\mathrm{V},k} \equiv \int_0^\infty V^k n_{\mathrm{V}}(V) \,\mathrm{d}V$$

and can be easily related to moments of length-based NDF:

$$m_{V,k} = \int_0^\infty (k_V L^3)^k n_L(L) \, \mathrm{d}L = k_V^k m_{L,3k}$$



# Mass-Based NDF

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Simple Example

- Mass-based NDF n<sub>M</sub>(M) is often preferred because mass is conserved quantity for complex shapes
- In case of fractal aggregates:  $M = k_{\rm M}L^{D_{\rm f}}$  where  $1 < D_{\rm f} \le 3$  is fractal dimension (sphere:  $D_{\rm f} = 3$ , diffusion-limited aggregate:  $D_{\rm f} = 1.8$ , etc.)
- Length-based and mass-based NDFs are related by  $n_{\rm L}(L) = D_{\rm f} k_{\rm M} L^{D_{\rm f}-1} n_{\rm M} (k_{\rm M} L^{D_{\rm f}})$
- Their moments are related by:  $m_{M,k} = k_M^k m_{L,D_fk}$
- It is often the case that in closed systems total particle mass is conserved, i.e., m<sub>M,1</sub> is constant
- In practical applications, choice of NDF with which to work often depends on which moments can be measured experimentally (e.g. light scattering ⇒ *L*, etc.)



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- Special case of considerable interest occurs when internal-coordinate vector is particle velocity vector: v
- Velocity-based NDF n<sub>U</sub>(t, x, v) is parameterized by 3 velocity components v = (v<sub>1</sub>, v<sub>2</sub>, v<sub>3</sub>)
- Total number concentration is defined by integrating over all possible values of particle velocity:

$$N = m_{\mathbf{U},0} \equiv \int_{\Omega_{\mathbf{v}}} n_{\mathbf{U}}(\mathbf{v}) \,\mathrm{d}\mathbf{v}$$

- Because particles may have different velocities, number-weighted particle velocity  $\mathbf{U}_{\mathrm{p}}$  can be calculated as:

$$\mathbf{U}_{\mathrm{p}} \equiv \frac{1}{N} \int_{\Omega_{\mathrm{v}}} \mathbf{v} n_{\mathrm{U}}(\mathbf{v}) \,\mathrm{d}\mathbf{v} = \frac{m_{\mathrm{U},1}}{m_{\mathrm{U},0}}$$

Number-weighted particle velocity is only used when all particles
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- NDF n<sub>ξ</sub> and velocity-based NDF n<sub>U</sub> have same mathematical meaning but particle velocity is a particular internal coordinate
- We distinguish between *passive* internal coordinates such as particle size, volume, area, or temperature, from *active* internal coordinates such as particle velocity
- In first case we refer to **population balance equation (PBE)** and in second to **generalized population balance equation** (**GPBE**)
- In PBE, velocity of disperse phase is assumed to be known and NDF can be treated as advected scalar field
- Scalar fields appearing in GPBE are usually active (i.e., momentum exchange between particles depends on internal coordinates such as length) and thus velocity of disperse phase must be computed from seperate momentum balance



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- Disperse multiphase systems can be modeled at different levels
  - **Microscale** simulations contain most detail, but are too expensive for most applications
  - **Mesoscale** simulations use physical approximations to formulate a PBE or GPBE for NDF
  - NDF can be univariate or multivariate, and definition is problem dependent
  - Thus, first step is to formulate a mesoscale model for polydisperse flows



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# MESOSCALE DESCRIPTION OF POLYDISPERSE FLOWS

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### Microscale versus Mesoscale versus Macroscale



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# Population Balance Equation

- PBE is simple continuity statement written in terms of NDF
- It can be derived as balance for particles in fixed finite control volume in physical space  $\Omega_x$  and in phase space  $\Omega_{\xi}$  with boundaries defined as  $\partial \Omega_x$  and  $\partial \Omega_{\xi}$ :

$$\begin{aligned} \frac{\partial}{\partial t} \left( \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\Omega_{\xi}} d\boldsymbol{\xi} \, n_{\xi} \right) + \int_{\Omega_{\xi}} d\boldsymbol{\xi} \int_{\partial\Omega_{\mathbf{x}}} n_{\xi} \mathbf{v} \cdot d\mathbf{A}_{\mathbf{x}} \\ &+ \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\partial\Omega_{\xi}} n_{\xi} \dot{\boldsymbol{\xi}} \cdot d\mathbf{A}_{\xi} = \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\Omega_{\xi}} d\boldsymbol{\xi} \, h_{\xi} \end{aligned}$$

 where v is (known) velocity vector for particulate system, ξ is continuous rate of change in phase space, and h<sub>ξ</sub> is discontinuous jump function representing discrete events



# Population Balance Equation

#### **Reynolds-Gauss theorem**

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Given control volume  $\Omega_x$  and its boundary  $\partial\Omega_x$  oriented by outward-pointing normals, flux of vector v across boundary is equal to volume integral of divergence of v (i.e.,  $\nabla_x \cdot v$ ) inside control volume

$$\int_{\partial\Omega_{\xi}}^{\infty} n_{\xi} \mathbf{v} \cdot d\mathbf{A}_{\mathbf{x}} = \int_{\Omega_{\mathbf{x}}} (\nabla_{\mathbf{x}} \cdot \mathbf{v} n_{\xi}) d\mathbf{x}$$
$$\int_{\partial\Omega_{\xi}} n_{\xi} \dot{\boldsymbol{\xi}} \cdot d\mathbf{A}_{\xi} = \int_{\Omega_{\xi}} \left( \frac{\partial}{\partial \boldsymbol{\xi}} \cdot \dot{\boldsymbol{\xi}} n_{\xi} \right) d\boldsymbol{\xi}$$

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# Population Balance Equation

 If Reynolds-Gauss theorem is applied, it is straightforward to obtain

$$\frac{\partial}{\partial t} \left( \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\Omega_{\xi}} d\boldsymbol{\xi} \, n_{\xi} \right) + \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\Omega_{\xi}} d\boldsymbol{\xi} \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v} \, n_{\xi} + \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\Omega_{\xi}} d\boldsymbol{\xi} \frac{\partial}{\partial \boldsymbol{\xi}} \cdot \dot{\boldsymbol{\xi}} \, n_{\xi} = \int_{\Omega_{\mathbf{x}}} d\mathbf{x} \int_{\Omega_{\xi}} d\boldsymbol{\xi} \, h_{\xi}$$

- $\frac{\partial}{\partial x} = \nabla_x = (\partial/\partial x_1, \partial/\partial x_2, \partial/\partial x_3)$  is gradient operator in physical space
- $\frac{\partial}{\partial \xi} = \nabla_{\xi} = (\partial/\partial \xi_1, \dots, \partial/\partial \xi_M)$  is gradient operator in phase space

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### **Population Balance Equation**

For any arbitrary control volumes Ω<sub>x</sub> and Ω<sub>ξ</sub>, integrand must satisfy relation

$$\frac{\partial n_{\xi}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v} \, n_{\xi} + \frac{\partial}{\partial \xi} \cdot \dot{\boldsymbol{\xi}} \, n_{\xi} = h_{\xi}$$

• Einstein notation (i.e., repeated Roman indices imply summation)

$$\frac{\partial n_{\xi}}{\partial t} + \frac{\partial}{\partial x_{i}} v_{i} n_{\xi} + \frac{\partial}{\partial \xi_{i}} \dot{\xi}_{i} n_{\xi} = h_{\xi}$$

 Very important is distinction between continuous processes (drift terms) and discontinuous processes (instantaneous jumps)



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### Generalized Population Balance Equation

 By using very similar approach it is possible to derive GPBE for NDF that includes particle velocity: n(t, x, v, ξ)

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v} \, n + \frac{\partial}{\partial \mathbf{v}} \cdot \mathbf{A}_{\mathrm{p}} n + \frac{\partial}{\partial \boldsymbol{\xi}} \cdot \dot{\boldsymbol{\xi}} \, n = h$$

- $A_p$  is continuous rate of change of particle velocity (i.e., acceleration) or force per unit mass acting on particles (e.g., gravity, fluid drag, etc.)
- Right-hand side *h* is discontinuous jump term, but now including discontinuous changes in particle momentum (e.g., collisions)



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Generalized Population Balance Equation

- Collision, aggregation, agglomeration, coalescence, breakup events can be described as discontinuous only when they occur on time and length scales that are much shorter than those characterizing changes in NDF
- This is indeed the case of particle–particle interactions via the hard-sphere potential (pure collisions) but with other potentials (i.e. soft-sphere potential) this may not be a good approximation
- In GPBE there are never terms for diffusion in physical space, however, there are often terms for diffusion in velocity phase space due to random (e.g., Brownian) forces, or to turbulent fluctuations in continuous phase due to drag



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#### When is CFD needed vs. well-stirred model?

- · Latex particles aggregation due to coagulant
- Aggregation rate depends on shear rate G seen by particles
- Aggregates breakup in high-shear regions
- Faster stirring results in faster mixing, but higher shear
- Latex concentration in feed affects aggregation rate
- Laser light scattering determines radius of gyration  $\langle R_g 
  angle \propto \langle L 
  angle$
- Three characeristic time scales: τ<sub>M</sub> mixing, τ<sub>A</sub> aggregation, τ<sub>B</sub> breakage



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Eventually aggregation and breakage balance each other and steady state is reached (dynamic equilibrium)



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- Here only one internal coordinate is considered, *ξ*, dimensionless mass of aggregate (i.e., actual mass divided by mass of primary particles)
- n(t, x, ξ) is Reynolds-averaged NDF often called cluster mass distribution (CMD)
- Reynolds-averaged PBE (neglecting fluctuations) is:

$$\begin{split} \frac{\partial n(t,\mathbf{x},\xi)}{\partial t} &+ \frac{\partial}{\partial x_i} \langle u_i \rangle n(t,\mathbf{x},\xi) - \frac{\partial}{\partial x_i} D_t \frac{\partial n(t,\mathbf{x},\xi)}{\partial x_i} = \\ &+ \frac{1}{2} \int_0^{\xi} k^A(G;\xi - \xi',\xi') n(t,\mathbf{x},\xi - \xi') n(t,\mathbf{x},\xi') \,\mathrm{d}\xi' \\ &- n(t,\mathbf{x},\xi) \int_0^{\infty} k^A(G;\xi,\xi') n(t,\mathbf{x},\xi') \,\mathrm{d}\xi' \\ &+ \int_{\xi}^{\infty} k^B(G;\xi') b(\xi|\xi') n(t,\mathbf{x},\xi') \,\mathrm{d}\xi' - k^B(G;\xi) n(t,\mathbf{x},\xi) \end{split}$$



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- $k^A(G;\xi,\xi')$  is aggregation kernel of two aggregates with masses  $\xi$  and  $\xi'$
- $k^B(G;\xi')$  is breakage kernel of aggregate of mass  $\xi'$
- $b(\xi|\xi')$  is daughter distribution function
- *G* is (turbulent) shear rate, a spatial dependent property [i.e.,  $G = G(\mathbf{x})$ ], that is driving force for turbulent aggregation and breakage defined as  $G = \left(\frac{\varepsilon}{\nu}\right)^{1/2}$
- It is usually quite easy to estimate volume-averaged shear rate in a vessel:  $\overline{G} = \left(\frac{P}{\rho V v}\right)^{1/2}$



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# A Simple Example: Particle Aggregation and Breakage in CSTR

When steady state is reached PBE can be easily made dimensionless by using volume-averaged total number density of aggregates,  $N_t$ , characteristic length scale (e.g. tank diameter), characteristic mixing time  $\tau_M$  and average mass of aggregates at steady state,  $\langle \xi \rangle$ :

$$\begin{split} \frac{\partial}{X_{i}}U_{i}N(\theta,\mathbf{X},\xi) &- \frac{\partial}{\partial X_{i}}\Gamma_{t}\frac{\partial N(\theta,\mathbf{X},\xi)}{\partial X_{i}} = \\ &+ \frac{\tau_{M}}{2\tau_{A}}\int_{0}^{\xi}K^{A}(G;\xi-\xi',\xi')N(\theta,\mathbf{X},\xi-\xi')N(\theta,\mathbf{X},\xi')\,\mathrm{d}\xi' \\ &- \frac{\tau_{M}}{\tau_{A}}N(\theta,\mathbf{X},\xi)\int_{0}^{\infty}K^{A}(G;\xi,\xi')N(\theta,\mathbf{X},\xi')\,\mathrm{d}\xi' \\ &+ \frac{\tau_{M}}{\tau_{B}}\int_{\xi}^{\infty}K^{B}(G;\xi')b(\xi|\xi')N(\theta,\mathbf{X},\xi')\,\mathrm{d}\xi' \\ &- \frac{\tau_{M}}{\tau_{B}}K^{B}(G;\xi)N(\theta,\mathbf{X},\xi) \end{split}$$



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$$N := \frac{n(\xi; \mathbf{x}, t)}{N_t}$$

$$X_i := \frac{x_i}{d}$$

$$U_i := \frac{\langle u_i \rangle}{d/\tau_M}$$

$$\Gamma_t := \frac{D_t}{d^2/\tau_M}$$

$$K^A := \frac{k^A(G; \xi, \xi')}{k^A(\overline{G}; \langle \xi \rangle, \langle \xi \rangle)}$$

$$K^B := \frac{k^B(G; \xi)}{k^B(\overline{G}; \langle \xi \rangle)}$$

Characteristic time for aggregation

$$\tau_A := \frac{1}{k^A(\overline{G}; \langle \xi \rangle, \langle \xi \rangle) N_t}$$

#### Characteristic time for breakage

$$\tau_B := \frac{1}{k^B(\overline{G}; \langle \xi \rangle)}$$

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 When mixing is much faster than aggregation τ<sub>M</sub> ≪ τ<sub>A</sub> and breakage τ<sub>M</sub> ≪ τ<sub>B</sub> spatial gradients of CMD are very small and problem can be solved in terms of volume-averaged CMD:

$$\overline{n}(t,\xi) = \frac{\int_{V} n(t,\mathbf{x},\xi) \,\mathrm{d}\mathbf{x}}{V}$$

• Its evolution is dictated by volume-averaged PBE:

$$\begin{split} \frac{\partial \overline{n}(t,\xi)}{\partial t} &= \frac{1}{2} \int_0^{\xi} \overline{k}^A(G;\xi-\xi',\xi') \overline{n}(t,\xi-\xi') \overline{n}(t,\xi') \,\mathrm{d}\xi' \\ &\quad -\overline{n}(t,\xi) \int_0^{\infty} \overline{k}^A(G;\xi,\xi') \overline{n}(t,\xi') \,\mathrm{d}\xi' \\ &\quad + \int_{\xi}^{\infty} \overline{k}^B(G;\xi') b(\xi|\xi') \overline{n}(t,\xi') \,\mathrm{d}\xi' - \overline{k}^B(G;\xi) \overline{n}(t,\xi) \end{split}$$

4 D b 4 B b 4 B b 4 B b

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Introduction to Disperse Multiphase Flows

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Simulation Methods

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Different Types of NDF

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Generalized Population Balance Equation

Simple Example



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• Volume-averaged aggregation kernel is

$$\overline{k}^{A}(G;\xi,\xi') = \int_{0}^{\infty} k^{A}(G^{*};\xi,\xi') f(G^{*}) \,\mathrm{d}G^{*} \neq k^{A}(\overline{G};\xi,\xi')$$

Volume-averaged breakage kernel is

$$\overline{k}^{B}(G;\xi) = \int_{0}^{\infty} k^{B}(G^{*};\xi) f(G^{*}) \,\mathrm{d}G^{*} \neq k^{B}(\overline{G};\xi)$$

• Distribution function  $f(G^*)$  accounts for fact that shear rate is not homogeneous in vessel



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#### Need for CFD depends on ratio between different time scales!



Marchisio et al. (2006) AIChE J. 52, 158

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Simple Example

- Disperse multiphase systems can be modeled at different levels of detail
- **Microscale** simulations contain most detail, but are too expensive for most applications
- **Mesoscale** simulations use physical approximations to formulate a PBE or GPBE for NDF
- Macroscale simulations use mathematical approximations to approximate unclosed moments of NDF
- Thus, first step is to formulate a mesoscale model for polydisperse flows



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#### Part 2

Computational Models for Polydisperse Particulate and Multiphase Systems

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Real-Space Advection

### **QUADRATURE-BASED MOMENT METHODS**

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### **Closure Problem**

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Quadrature-Based Moment Methods

Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations

Real-Space Advection Closure problem appears always in following form:

$$I = \int_{\Omega_{\xi}} n(\xi) g(\xi) \,\mathrm{d}\xi$$

where  $n(\xi)$  is unknown univariate NDF and  $\Omega_{\xi}$  is integration interval

#### QBMM use a Gaussian quadrature

In Gaussian quadrature theory NDF is weight function or measure for which integer moments

$$m_k = m(k) = \langle \xi^k \rangle := \int_{\Omega_{\varepsilon}} n(\xi) \, \xi^k \, \mathrm{d}\xi \quad k = 0, 1, 2, \dots$$

#### must exist



Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem

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Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations Real-Space Advection A set of polynomials  $\{P_0(\xi), P_1(\xi), \dots, P_{\alpha}(\xi), \dots\}$  with

$$P_{\alpha}(\xi) = k_{\alpha,0}\xi^{\alpha} + k_{\alpha,1}\xi^{\alpha-1} + \dots + k_{\alpha,\alpha}$$

is orthogonal in integration interval  $\Omega_{\boldsymbol{\xi}},$  with respect to weight function, if

$$\int_{\Omega_{\xi}} n(\xi) P_{\alpha}(\xi) P_{\beta}(\xi) \, \mathrm{d}\xi \begin{cases} = 0 & \text{for } \alpha \neq \beta \\ > 0 & \text{for } \alpha = \beta \end{cases}$$

and, of course, is said to be orthonormal if

$$\int_{\Omega_{\xi}} n(\xi) P_{\alpha}(\xi) P_{\beta}(\xi) \, \mathrm{d}\xi = \begin{cases} 0 & \text{for } \alpha \neq \beta \\ 1 & \text{for } \alpha = \beta \end{cases}$$



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Advection

Any set of orthogonal polynomials  $\{P_{\alpha}(\xi)\}\$  has recurrence formula relating three consecutive polynomials in a sequence:

$$P_{\alpha+1}(\xi) = (\xi - a_{\alpha})P_{\alpha}(\xi) - b_{\alpha}P_{\alpha-1}(\xi) \quad \alpha = 0, 1, 2, \dots$$

with  $P_{-1}(\xi) \equiv 0$  and  $P_0(\xi) \equiv 1$  and

$$a_{\alpha} = \frac{\int_{\Omega_{\xi}} n(\xi)\xi P_{\alpha}(\xi)P_{\alpha}(\xi) \,\mathrm{d}\xi}{\int_{\Omega_{\xi}} n(\xi)P_{\alpha}(\xi)P_{\alpha}(\xi) \,\mathrm{d}\xi} \quad \text{for } \alpha = 0, 1, 2, \dots$$
$$b_{\alpha} = \frac{\int_{\Omega_{\xi}} n(\xi)P_{\alpha}(\xi)P_{\alpha}(\xi) \,\mathrm{d}\xi}{\int_{\Omega_{\xi}} n(\xi)P_{\alpha-1}(\xi)P_{\alpha-1}(\xi) \,\mathrm{d}\xi} > 0 \quad \text{for } \alpha = 1, 2, \dots$$

One can calculate  $a_0$ , then  $P_1(\xi)$ , then  $a_1$  and  $b_1$  and so on ...



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Real-Space

- Coefficients  $a_{\alpha}$  and  $b_{\alpha}$  can be written in terms of moments
- Coefficients necessary for construction of polynomial of order *N* can be calculated from first 2*N* 1 moments of NDF
- For example with  $m_0$ ,  $m_1$ ,  $m_2$  and  $m_3$ , it is possible to calculate the following coefficients:

$$a_{0} = \frac{m_{1}}{m_{0}}$$

$$a_{1} = \frac{m_{3}m_{0}^{2} + m_{1}^{3} - 2m_{2}m_{1}m_{0}}{m_{2}m_{0} + m_{1}^{2} - 2m_{1}^{2}m_{0}}$$

$$b_{1} = \frac{m_{2}m_{0} + m_{1}^{2} - 2m_{1}^{2}m_{0}}{m_{0}^{2}}$$

which suffice for calculation of polynomial  $P_2(\xi)$ 

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#### Quadrature Theory

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4 D b 4 B b 4 B b 4 B b



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#### **Quadrature-Based Moment Methods**

# Why are we interested in orthogonal polynomials?



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#### **Quadrature-Based Moment Methods**

• Closure problem can be overcome by using a quadrature formula:

$$\int_{\Omega_{\xi}} n(\xi) g(\xi) \, \mathrm{d}\xi \approx \sum_{\alpha=1}^{N} w_{\alpha} g(\xi_{\alpha})$$

where  $w_{\alpha}$  and  $\xi_{\alpha}$  are weights and nodes/abscissas of quadrature formula, and *N* is number of nodes

- Accuracy of quadrature formula is quantified by its degree of accuracy
- Degree of accuracy is equal to d if quadrature formula is exact when the integrand is a polynomial of order less than or equal to d and there exists at least one polynomial of order d + 1 that makes quadrature formula inexact



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Moment Transport Equations Real-Space Advection **Quadrature-Based Moment Methods** 

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#### **Quadrature-Based Moment Methods**

#### GAUSSIAN QUADRATURE

Necessary and sufficient condition for following formula:

$$\int_{\Omega_{\xi}} n(\xi) g(\xi) \,\mathrm{d}\xi = \sum_{\alpha=1}^{N} g(\xi_{\alpha}) w_{\alpha} + R_{N}(g)$$

to be Gaussian quadrature approximation or, equivalently, that it has degree of accuracy of 2N - 1, is that its nodes  $\{\xi_{\alpha}\}$  coincide with the N roots of polynomial  $P_N(\xi)$  of order N orthogonal in  $\Omega_{\xi}$  with respect to weight function  $n(\xi)$ 



### Computing Quadrature Approximation

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#### HOW DO WE CALCULATE THE QUADRATURE APPROX?

*N* weights and *N* abscissas can be determined by solving a non-linear system:

$$m_0 = \sum_{\alpha=1}^N w_\alpha$$
$$m_1 = \sum_{\alpha=1}^N w_\alpha \xi_\alpha$$

$$m_{2N-1} = \sum_{\alpha=1}^{N} w_{\alpha} \xi_{\alpha}^{2N-1}$$

using Newton-Raphson method, or any other non-linear equation solver (very good initial guess needed to ensure convergence!)



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Advection

Better way is to employ recursive relationship for orthogonal polynomials:

$$\xi \begin{bmatrix} P_0(\xi) \\ P_1(\xi) \\ \vdots \\ P_{N-2}(\xi) \\ P_{N-1}(\xi) \end{bmatrix} = \begin{bmatrix} a_0 & 1 & & & \\ b_1 & a_1 & 1 & & \\ & & \ddots & & \\ & & & \ddots & 1 \\ & & & & \ddots & 1 \\ & & & & a_{N-1} \end{bmatrix} \begin{bmatrix} P_0(\xi) \\ P_1(\xi) \\ \vdots \\ P_{N-2}(\xi) \\ P_{N-1}(\xi) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ P_{N}(\xi) \end{bmatrix}$$

Nodes of quadrature approximation  $\{\xi_{\alpha}\}$  (i.e., roots of  $P_N(\xi)$ ), are eigenvalues of tridiagonal matrix appearing above Matrix is re-written in terms of equivalent tridiagonal symmetric (Jacobi) matrix



# Computing Quadrature Approximation

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Advection

Better way is to employ recursive relationship for orthogonal polynomials:

	$ \begin{array}{c} P_0(\xi) \\ P_1(\xi) \end{array} $		$b_1$	$\frac{1}{a_1}$	1			$\left[\begin{array}{c} P_0(\xi) \\ P_1(\xi) \end{array}\right]$		0 0	
ξ	÷	=				·		:	+	:	
	$P_{N-2}(\xi)$					۰.	1	$P_{N-2}(\xi)$		0	
	$P_{N-1}(\xi)$						$a_{N-1}$	$[P_{N-1}(\xi)]$	I	$P_N(\xi)$	

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Advection

# Computing Quadrature Approximation

Matrix can be made symmetric (preserving eigenvalues) by a diagonal similarity transformation to give a Jacobi matrix:



Procedure transforms ill-conditioned problem of finding roots of polynomial into well-conditioned problem of finding eigenvalues and eigenvectors of tridiagonal symmetric matrix

*N* weights are calculated as  $w_{\alpha} = m_0 \varphi_{\alpha 1}^2$  where  $\varphi_{\alpha 1}$  is first component of  $\alpha^{\text{th}}$  eigenvector  $\varphi_{\alpha}$  of Jacobi matrix



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Quadrature-**Based Moment** Methods **Closure Problem** Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPRE for Eluid\_Particle Systems Moment Transport Equations **Beal-Space** 

Advection

**1** Construct matrix **P** with components  $P_{\alpha,\beta}$ :

$$P_{\alpha,\beta} = P_{1,\beta-1}P_{\alpha+1,\beta-2} - P_{1,\beta-2}P_{\alpha+1,\beta-1}$$
  
$$\beta \in 3, \dots, 2N+1 \text{ and } \alpha \in 1, \dots, 2N+2-\beta$$

$$P_{\alpha,1} = \delta_{\alpha 1} \quad \alpha \in 1, \dots, 2N+1$$

$$P_{\alpha,2} = (-1)^{\alpha-1} m_{\alpha-1} \quad \alpha \in 1, \dots, 2N$$

$$\zeta_{\alpha} = \frac{P_{1,\alpha+1}}{P_{1,\alpha}P_{1,\alpha-1}} \quad \alpha \in 2, \dots, 2N$$



Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-**Based Moment** Methods **Closure Problem** Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPRE for Eluid\_Particle Systems Moment Transport Equations **Beal-Space** 

Advection

**1** Construct matrix **P** with components  $P_{\alpha,\beta}$ :

$$P_{\alpha,\beta} = P_{1,\beta-1}P_{\alpha+1,\beta-2} - P_{1,\beta-2}P_{\alpha+1,\beta-1}$$
  
$$\beta \in 3, \dots, 2N+1 \text{ and } \alpha \in 1, \dots, 2N+2-\beta$$

#### first row of matrix is

$$P_{\alpha,1} = \delta_{\alpha 1} \quad \alpha \in 1, \dots, 2N+1$$

$$P_{\alpha,2} = (-1)^{\alpha-1} m_{\alpha-1} \quad \alpha \in 1, \dots, 2N$$

$$\zeta_{\alpha} = \frac{P_{1,\alpha+1}}{P_{1,\alpha}P_{1,\alpha-1}} \quad \alpha \in 2, \dots, 2N$$



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Real-Space Advection **1** Construct matrix **P** with components  $P_{\alpha,\beta}$ :

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$$P_{\alpha,1} = \delta_{\alpha 1} \quad \alpha \in 1, \dots, 2N+1$$

**3**  $\delta_{\alpha 1}$  is Kronecker delta and components in second column of **P** are

$$P_{\alpha,2} = (-1)^{\alpha-1} m_{\alpha-1} \quad \alpha \in 1, \dots, 2N$$

Calculate coefficients of continued fraction  $\{\zeta_{\alpha}\}$ :

$$\zeta_{\alpha} = \frac{P_{1,\alpha+1}}{P_{1,\alpha}P_{1,\alpha-1}} \quad \alpha \in 2, \dots, 2N$$



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Quadrature-Based Moment Methods

Computing Quadrature Approximation

**Realizable Moments** 

Generalized Population Balance Equation NDF for Fluid–Particle Systems GPBE for Fluid–Particle Systems Moment Transport Equations Real-Space Advection

### Product-Difference Algorithm

 Coefficients of Jacobi matrix are obtained from sums and products of ζ<sub>α</sub>:

$$a_{\alpha} = \zeta_{2\alpha} + \zeta_{2\alpha-1} \quad \alpha \in 1, \dots, N$$

$$b_{\alpha} = \sqrt{\zeta_{2\alpha+1}\zeta_{2\alpha}} \quad \alpha \in 1, \dots, N-1$$

**2** For example with N = 2, **P** matrix is

 $\begin{bmatrix} 1 & m_0 & m_1 & m_0m_2 - m_1^2 & m_0 \left(m_3m_1 - m_2^2\right) \\ 0 & -m_1 & -m_2 & -\left(m_0m_3 - m_2m_1\right) \\ 0 & m_2 & m_3 \\ 0 & -m_3 \\ 0 \end{bmatrix}$ 



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Quadrature-Based Moment Methods

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### Product-Difference Algorithm

Consider a normal (or Gaussian) distribution:

$$n(\xi) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(\xi - \mu\right)^2\right)}{2\sigma^2}\right)$$

Moments of distribution:

$$m_{0} = 1 \quad m_{1} = \mu \quad m_{2} = \mu^{2} + \sigma^{2}$$

$$m_{3} = \mu^{3} + 3\mu\sigma^{2}$$

$$m_{4} = \mu^{4} + 6\mu^{2}\sigma^{2} + 3\sigma^{4}$$

$$m_{5} = \mu^{5} + 10\mu^{3}\sigma^{2} + 15\mu\sigma^{4}$$

$$m_{6} = \mu^{6} + 15\mu^{4}\sigma^{2} + 45\mu^{2}\sigma^{4} + 15\sigma^{6}$$

$$m_{7} = \mu^{7} + 21\mu^{5}\sigma^{2} + 105\mu^{3}\sigma^{4} + 105\mu\sigma^{6}$$

$$m_{8} = \mu^{8} + 28\mu^{6}\sigma^{2} + 210\mu^{4}\sigma^{4} + 420\mu^{2}\sigma^{6} + 105\sigma^{8}$$

Use PD algorithm to calculate quadrature approximation of order four (i.e., N = 4) for  $\mu = 5$  and  $\sigma = 1$ 



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Quadrature-Based Moment Methods Closure Problem

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Advection

Product-Difference Algorithm

First eight moments of distribution are needed:

 $m_0 = 1$   $m_1 = 5$   $m_2 = 26$   $m_3 = 140$  $m_4 = 778$  $m_5 = 4450$  $m_6 = 26140$  $m_7 = 157400$ 

After applying PD algorithm Jacobi matrix is obtained:

	[5	1	0	0 ]
т	1	5	$\sqrt{2}$	0
J =	0	$\sqrt{2}$	5	$\sqrt{3}$
	0	0	$\sqrt{3}$	5

resulting in:  $w_1 = 0.0459$ ,  $w_2 = 0.4541$ ,  $w_3 = 0.4541$ ,  $w_4 = 0.0459$ , and  $\xi_1 = 2.6656$ ,  $\xi_2 = 4.2580$ ,  $\xi_3 = 5.7420$ ,  $\xi_4 = 7.3344$ 



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#### Product-Difference Algorithm

PD algorithm works well when  $\xi$  is positive, but not when distribution has zero mean (moment of order one null) Example: Gaussian distribution with  $\mu = 0$  and  $\sigma = 1$ 

$m_0$	=	1
$m_1$	=	0
$m_2$	=	1
$m_3$	=	0
$m_4$	=	3
$m_5$	=	0
<i>m</i> <sub>6</sub>	=	15
$m_7$	=	0

In general, Wheeler algorithm should be used (see Numerical Recipes for details)



#### **Realizable Moments**

Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations Real-Space Advection Moment inversion algorithm only works if moments are realizable

Definition: Realizable moments correspond to a non-negative NDF

Hankel matrices are used to check if moments  $\{m_0, m_1, \ldots, m_{2N}\}$  are realizable:

	$m_0$	$m_1$	$m_2$	•••	$m_N$
	$m_1$	$m_2$	$m_3$	•••	$m_{N+1}$
$\mathbf{H}_N :=$	$m_2$	$m_3$	·		$m_{N+2}$
	:	÷	÷	·.	÷
	$m_N$	$m_{N+1}$	$m_{N+2}$		$m_{2N}$

Moment set  $\{m_0, m_1, \ldots, m_{2N}\}$  is realizable iff  $|\mathbf{H}_N| \ge 0$ 

With *N*-node QMOM,  $|\mathbf{H}_N| = 0$ , but  $|\mathbf{H}_n| > 0$  for n = 0, 1, ..., N - 1



#### Realizable Moments

Example for N = 2:

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$$\begin{aligned} |\mathbf{H}_0| &= m_0 \\ |\mathbf{H}_1| &= m_0 m_2 - m_1^2 \\ |\mathbf{H}_2| &= m_4 (m_0 m_2 - m_1^2) - m_3 (m_0 m_3 - m_1 m_2) + m_2 (m_1 m_3 - m_2^2) \end{aligned}$$

Or, using central moments,  $C_0 = 1$ ,  $C_1 = 0$ ,  $C_2 = variance$ :

$$|\mathbf{H}_0| = 1$$
  
 $|\mathbf{H}_1| = C_2$   
 $|\mathbf{H}_2| = C_4 C_2 - C_3^2 - C_2^3$ 

With 2-node QMOM,  $|\mathbf{H}_2| = 0$ , and  $n^*(\xi) = w_1\delta(\xi - \xi_1) + w_2\delta(\xi - \xi_2)$ When  $|\mathbf{H}_N| = 0$ , but  $|\mathbf{H}_n| > 0$  for n = 0, 1, ..., N - 1; we say that moments are on boundary of moment space



#### Moment Space

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Advection

Moment vectors M = {m<sub>0</sub>, m<sub>1</sub>, ..., m<sub>2N</sub>} live in finite moment space:
Moment space is convex: let M<sub>1</sub> and M<sub>2</sub> be two sets of

 Moment space is convex: let M<sub>1</sub> and M<sub>2</sub> be two sets of realizable moments, then M\* = a<sub>1</sub>M<sub>1</sub> + a<sub>2</sub>M<sub>2</sub> is realizable when a<sub>1</sub> and a<sub>2</sub> are non-negative

• If  $|\mathbf{H}_N| = 0$ , then **M** is on boundary of moment space

• If  $|\mathbf{H}_N| = 0$ , then  $m_{2N}$  has smallest possible value

• If  $|\mathbf{H}_N| = 0$ , then  $n^*$  is sum of N weighted delta functions

• If  $|\mathbf{H}_N| > 0$ , then **M** is in interior of moment space

• If  $|\mathbf{H}_N| > 0$ , then  $n^*(\xi)$  is continuous function of  $\xi$ 

Quadrature-Based Moment Methods reconstruct  $n^*(\xi)$  for the boundary of moment space by satisfying all moments  $\{m_0, m_1, \dots, m_{2N-1}\}$ 



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Advection

Variation: Gauss-Radau Quadrature

- In many cases, it is advantageous to include even-numbered moment m<sub>2N</sub>: evaporation, nucleation, spatial fluxes, reconstruct continuous NDF (EQMOM), etc.
- Moment set  $\mathbf{M} = \{m_0, m_1, \dots, m_{2N}\}$  has 2N + 1 degrees of freedom
- Gauss–Radau quadrature fixes one node ξ<sub>0</sub>, but weight w<sub>0</sub> is free:

$$\int g(\xi)n(\xi) \,\mathrm{d}\xi = \sum_{i=0}^N w_i g(\xi_i)$$

e.g.,  $\xi_0$  is smallest particle mass in system

• There are N + 1 weights  $w_i$  and N nodes  $\xi_i$  that must be found from moments for k = 0, 1, ..., 2N:

$$m_k := \int \xi^k n(\xi) \, \mathrm{d}\xi = \sum_{i=0}^N w_i \xi_i^k$$

• Small change in Wheeler algorithm (see Numerical Recipes)



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# Summary of QBMM for Solving PBE

• Starting from PBE for  $n(t,\xi)$ , formally derived unclosed moment equations  $\mathbf{M}(t) = \{m_0(t), m_1(t), \dots, m_k(t)\} | k = 0, 1, \dots, 2N$ :

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = S_k(\mathbf{M}) \quad \Longrightarrow \quad \frac{\mathrm{d}\mathbf{M}}{\mathrm{d}t} = \mathbf{S}(\mathbf{M})$$

• Close moment equations with quadrature:

$$n(t,\xi) \approx n^*(t,\xi) = \sum_{i=0}^N w_i \delta(\xi - \xi_i)$$

where  $w_i$  and  $\xi_i$  are found from  $\mathbf{M}(t)$  with Wheeler algorithm

• Use numerical ODE solver to advance in time:

 $\mathbf{M}(t + \Delta t) = \mathbf{M}(t) + \mathbf{S}(\mathbf{M}(t))\Delta t$ 

#### given initial conditions $\mathbf{M}(0)$

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#### GENERALIZED POPULATION BALANCE EQUATION

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#### From Microscale to Mesoscale Model

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Generalized Population Balance Equation

NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems

Moment Transport Equations Real-Space Advection Microscale Description

Define phase space of *mesoscale* variables needed to describe a "particle" (velocity, volume, etc.) Model changes to *one* particle's mesoscale variables due to all other particles, fluid, body forces, etc. (one-particle density function)

Mesoscale Model

Closure occurs at the level of the one-particle density function

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#### Computational Models for Polydisperse Particulate and Multiphase Systems

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Real-Space Advection

## NDF for Fluid–Particle Systems

- Let us consider population of N<sub>p</sub> particles characterized by variables: position {X<sup>(n)</sup>}, velocity {U<sub>p</sub><sup>(n)</sup>} and composition {ξ<sub>p</sub><sup>(n)</sup>}
- State of *n*<sup>th</sup> particle will change according to following Lagrangian (following particle) equations:

$$\frac{\mathrm{d}\mathbf{X}^{(n)}}{\mathrm{d}t} = \mathbf{U}_{\mathrm{p}}^{(n)}$$
$$\frac{\mathrm{d}\mathbf{U}_{\mathrm{p}}^{(n)}}{\mathrm{d}t} = \mathbf{A}_{\mathrm{fp}}^{(n)} + \mathbf{A}_{\mathrm{p}}^{(n)} + \mathbf{C}_{\mathrm{p}U}^{(n)}$$
$$\frac{\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}}^{(n)}}{\mathrm{d}t} = \mathbf{G}_{\mathrm{p}}^{(n)} + \mathbf{C}_{\mathrm{p}\boldsymbol{\xi}}^{(n)}$$

- Operators on right-hand sides (**mesoscale models**) depend on complete set of variables for all particles
- In principle, they can be found from microscale simulations



Computational Models for Polydisperse Particulate and Multiphase Systems

Rodney O. Fox International Francqui Professor

Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation

NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations

Real-Space Advection

- Let us consider population of N<sub>p</sub> particles characterized by variables: position {X<sup>(n)</sup>}, velocity {U<sub>p</sub><sup>(n)</sup>} and composition {ξ<sub>p</sub><sup>(n)</sup>}
- State of *n*<sup>th</sup> particle will change according to following Lagrangian (following particle) equations:

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Generalized Population Balance Equation

NDF for Fluid–Particle Systems GPBE for

Fluid–Particle Systems

Moment Transport Equations Real-Space Advection  Let us consider population of N<sub>p</sub> particles characterized by variables: position {X<sup>(n)</sup>}, velocity {U<sub>p</sub><sup>(n)</sup>} and composition {ξ<sub>p</sub><sup>(n)</sup>}

• State of *n*<sup>th</sup> particle will change according to following Lagrangian (following particle) equations:

$$\begin{aligned} \frac{\mathrm{d}\mathbf{X}^{(n)}}{\mathrm{d}t} &= \mathbf{U}_{\mathrm{p}}^{(n)} \\ \frac{\mathrm{d}\mathbf{U}_{\mathrm{p}}^{(n)}}{\mathrm{d}t} &= \mathbf{A}_{\mathrm{fp}}^{(n)} + \mathbf{A}_{\mathrm{p}}^{(n)} + \mathbf{C}_{\mathrm{p}U}^{(n)} \\ \frac{\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}}^{(n)}}{\mathrm{d}t} &= \mathbf{G}_{\mathrm{p}}^{(n)} + \mathbf{C}_{\mathrm{p}\boldsymbol{\xi}}^{(n)} \end{aligned}$$

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Moment Transport Equations Beal-Space

Advection

- Let us consider population of N<sub>p</sub> particles characterized by variables: position {X<sup>(n)</sup>}, velocity {U<sub>p</sub><sup>(n)</sup>} and composition {ξ<sub>p</sub><sup>(n)</sup>}
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Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population

Balance Equation

NDF for Fluid–Particle Systems GPBE for Fluid–Particle Systems Moment Transport Equations Real-Space

Advection

 In most descriptions of fluid–particle flows, mesoscale fluid–particle acceleration A<sup>(n)</sup><sub>fp</sub> includes a drag term of form

 $\mathbf{A}_{\rm fp}^{(n)}(t) \propto C_{\rm D}^{(n)} \left| \mathbf{U}_{\rm f}^{(n)}(t) - \mathbf{U}_{\rm p}^{(n)}(t) \right| \left[ \mathbf{U}_{\rm f}^{(n)}(t) - \mathbf{U}_{\rm p}^{(n)}(t) \right]$ 

where  $C_{\rm D}^{(n)}$  is drag coefficient, and  $\mathbf{U}_{\rm f}^{(n)}(t)$  is characteristic fluid velocity in neighborhood of  $\mathbf{X}^{(n)}(t)$ 

- $\mathbf{U}_{f}^{(n)}(t) = \mathbf{U}_{f}(t, \mathbf{X}^{(n)}(t)) + \mathbf{u}_{f}^{\prime(n)}(t)$  is called "fluid velocity seen by  $n^{\text{th}}$  solid particle", which is difficult to model *a priori* but is included in set of particle properties to be tracked
- In general it will be necessary to introduce some additional internal coordinates representing other fluid properties seen by n<sup>th</sup> particle: ξ<sup>(n)</sup><sub>ε</sub>



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Generalized Population Balance Equation

NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations

Real-Space Advection  In most descriptions of fluid–particle flows, mesoscale fluid–particle acceleration A<sup>(n)</sup><sub>fp</sub> includes a drag term of form

$$\mathbf{A}_{\rm fp}^{(n)}(t) \propto C_{\rm D}^{(n)} \left| \mathbf{U}_{\rm f}^{(n)}(t) - \mathbf{U}_{\rm p}^{(n)}(t) \right| \left[ \mathbf{U}_{\rm f}^{(n)}(t) - \mathbf{U}_{\rm p}^{(n)}(t) \right]$$

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- $\mathbf{U}_{f}^{(n)}(t) = \mathbf{U}_{f}(t, \mathbf{X}^{(n)}(t)) + \mathbf{u}_{f}^{\prime(n)}(t)$  is called "fluid velocity seen by  $n^{\text{th}}$  solid particle", which is difficult to model *a priori* but is included in set of particle properties to be tracked
  - In general it will be necessary to introduce some additional internal coordinates representing other fluid properties seen by n<sup>th</sup> particle: ξ<sup>(n)</sup><sub>f</sub>



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Equations Real-Space

Advection

 In most descriptions of fluid–particle flows, mesoscale fluid–particle acceleration A<sup>(n)</sup><sub>fp</sub> includes a drag term of form

$$\mathbf{A}_{\rm fp}^{(n)}(t) \propto C_{\rm D}^{(n)} \left| \mathbf{U}_{\rm f}^{(n)}(t) - \mathbf{U}_{\rm p}^{(n)}(t) \right| \left[ \mathbf{U}_{\rm f}^{(n)}(t) - \mathbf{U}_{\rm p}^{(n)}(t) \right]$$

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- $\mathbf{U}_{f}^{(n)}(t) = \mathbf{U}_{f}(t, \mathbf{X}^{(n)}(t)) + \mathbf{u}_{f}^{\prime(n)}(t)$  is called "fluid velocity seen by  $n^{\text{th}}$  solid particle", which is difficult to model *a priori* but is included in set of particle properties to be tracked
- In general it will be necessary to introduce some additional internal coordinates representing other fluid properties seen by *n*<sup>th</sup> particle: ξ<sup>(n)</sup><sub>f</sub>



Computational Models for

#### NDF for Fluid–Particle Systems

Polydisperse Particulate and Multiphase Systems State of N<sub>p</sub> particles immersed in defined by multi-particle-fluid

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation

NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations

Real-Space Advection  State of N<sub>p</sub> particles immersed in continuous phase is completely defined by *multi-particle-fluid joint PDF*:

$$\begin{split} f_{N_{p}}\left(t, \{\mathbf{x}^{(n)}\}, \{\mathbf{V}_{p}^{(n)}\}, \{\mathbf{\eta}_{p}^{(n)}\}, \{\mathbf{V}_{f}^{(n)}\}, \{\mathbf{\eta}_{f}^{(n)}\}\right) \, \mathrm{d}\{\mathbf{x}^{(n)}\} \, \mathrm{d}\{\mathbf{V}_{p}^{(n)}\} \, \mathrm{d}\{\mathbf{V}_{f}^{(n)}\} \, \mathrm{d}\{\mathbf{\eta}_{f}^{(n)}\} \\ & := \\ P\left[\cap_{n=1}^{N_{p}}\left\{\left(\mathbf{x}^{(n)} < \mathbf{X}^{(n)}(t) \le \mathbf{x}^{(n)} + \mathrm{d}\mathbf{x}^{(n)}\right) \right. \right. \right. \\ & \text{particle positions} \end{split}$$

$$\begin{split} & \Gamma\left[\Gamma_{n=1}\left\{\left(\mathbf{x}^{(n)} < \mathbf{x}^{(n)}\right) \le \mathbf{x}^{(n)} + d\mathbf{V}_{p}^{(n)}\right) & \text{particle positions} \\ & \cap\left(\mathbf{V}_{p}^{(n)} < \mathbf{U}_{p}^{(n)}(t) \le \mathbf{V}_{p}^{(n)} + d\mathbf{V}_{p}^{(n)}\right) & \text{particle velocities} \\ & \cap\left(\boldsymbol{\eta}_{p}^{(n)} < \boldsymbol{\xi}_{p}^{(n)}(t) \le \boldsymbol{\eta}_{p}^{(n)} + d\mathbf{V}_{p}^{(n)}\right) & \text{particle compositions} \\ & \cap\left(\mathbf{V}_{f}^{(n)} < \mathbf{U}_{f}^{(n)}(t) \le \mathbf{V}_{f}^{(n)} + d\mathbf{V}_{f}^{(n)}\right) & \text{seen fluid velocities} \\ & \cap\left(\boldsymbol{\eta}_{f}^{(n)} < \boldsymbol{\xi}_{f}^{(n)}(t) \le \boldsymbol{\eta}_{f}^{(n)} + d\boldsymbol{\eta}_{f}^{(n)}\right)\right) & \text{seen fluid compositions} \end{split}$$

In principle, it is known from microscale simulations



#### Computational Models for Polydisperse Particulate and Multiphase Systems

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# NDF for Fluid–Particle Systems

• Multi-particle joint PDF can be reduced to **single-particle joint PDF** by integrating out state variables for all particles except *n*<sup>th</sup>:

$$\begin{split} & f_{1}^{(m)}\left(t,\mathbf{x}^{(m)},\mathbf{V}_{p}^{(m)},\boldsymbol{\eta}_{p}^{(m)},\mathbf{V}_{f}^{(m)},\boldsymbol{\eta}_{f}^{(m)}\right) := \\ & \int_{m\neq n} f_{N_{p}}\left(t,\{\mathbf{x}^{(m)}\},\{\mathbf{V}_{p}^{(m)}\},\{\boldsymbol{\eta}_{p}^{(m)}\},\{\mathbf{V}_{f}^{(m)}\},\{\boldsymbol{\eta}_{f}^{(m)}\}\right) \,\mathrm{d}\mathbf{x}^{(m)} \,\mathrm{d}\mathbf{V}_{p}^{(m)} \,\mathrm{d}\boldsymbol{\eta}_{p}^{(m)} \,\mathrm{d}\mathbf{V}_{f}^{(m)} \,\mathrm{d}\boldsymbol{\eta}_{f}^{(m)} \end{split}$$

• Fluid-particle NDF is therefore defined as

$$n(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}}) := \sum_{n=1}^{N_{\mathrm{p}}} f_{1}^{(n)}(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}})$$

• In limit of identically distributed particles NDF becomes:

$$n(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}}) = N_{\mathrm{p}} f_{1}(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}})$$

#### i.e. numbering is arbitrary

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Computational Models for

Polydisperse Particulate and

Multiphase Systems Rodney O. Fox International Francoui NDF for Fluid–Particle Systems

 Multi-particle joint PDF can be reduced to single-particle joint PDF by integrating out state variables for all particles except n<sup>th</sup>:

$$\begin{split} f_1^{(n)}\left(t, \mathbf{x}^{(n)}, \mathbf{V}_{\rm p}^{(n)}, \boldsymbol{\eta}_{\rm p}^{(n)}, \mathbf{V}_{\rm f}^{(n)}, \boldsymbol{\eta}_{\rm f}^{(n)}\right) &:= \\ \int_{m \neq n} f_{N_{\rm p}}\left(t, \{\mathbf{x}^{(m)}\}, \{\mathbf{V}_{\rm p}^{(m)}\}, \{\boldsymbol{\eta}_{\rm p}^{(m)}\}, \{\mathbf{\eta}_{\rm f}^{(m)}\}, \{\boldsymbol{\eta}_{\rm f}^{(m)}\}\right) \, \mathrm{d}\mathbf{x}^{(m)} \, \mathrm{d}\mathbf{V}_{\rm p}^{(m)} \, \mathrm{d}\mathbf{V}_{\rm f}^{(m)} \, \mathrm{d}\mathbf{V}_{\rm f}^{(m)} \, \mathrm{d}\mathbf{\eta}_{\rm f}^{(m)} \, \mathrm{d}\mathbf{\eta}_{\rm f}^{(m)} \, \mathrm{d}\mathbf{V}_{\rm f}^{(m)} \, \mathrm{d}\mathbf{\eta}_{\rm f}^{(m)} \, \mathrm{d}\mathbf{v}_{\rm f}^{(m)} \, \mathrm{d$$

Fluid-particle NDF is therefore defined as

$$n(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}}) := \sum_{n=1}^{N_{\mathrm{p}}} f_{1}^{(n)}(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}})$$

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#### i.e. numbering is arbitrary

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- Professor Quadrature-Based Moment Methods Closure Problem Computing Quadrature
- Approximation Realizable Moments

#### Generalized Population

Balance Equation

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Real-Space Advection



Computational Models for

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Closure Problem Computing Quadrature Approximation Realizable Moments Generalized Population Balance Equation

NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations Real-Space Advection NDF for Fluid–Particle Systems

 Multi-particle joint PDF can be reduced to single-particle joint PDF by integrating out state variables for all particles except n<sup>th</sup>:

$$\begin{split} f_{1}^{(n)}\left(t,\mathbf{x}^{(n)},\mathbf{V}_{p}^{(n)},\boldsymbol{\eta}_{p}^{(n)},\mathbf{V}_{f}^{(n)},\boldsymbol{\eta}_{f}^{(n)}\right) &:= \\ & \int_{m\neq n} f_{N_{p}}\left(t,\{\mathbf{x}^{(m)}\},\{\mathbf{V}_{p}^{(m)}\},\{\boldsymbol{\eta}_{p}^{(m)}\},\{\mathbf{V}_{f}^{(m)}\},\{\boldsymbol{\eta}_{f}^{(m)}\}\right) \,\mathrm{d}\mathbf{x}^{(m)} \,\mathrm{d}\mathbf{V}_{p}^{(m)} \,\mathrm{d}\boldsymbol{\eta}_{p}^{(m)} \,\mathrm{d}\mathbf{V}_{f}^{(m)} \,\mathrm{d}\boldsymbol{\eta}_{f}^{(m)} \end{split}$$

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In limit of identically distributed particles NDF becomes:

$$n(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}}) = N_{\mathrm{p}}f_{1}(t, \mathbf{x}, \mathbf{v}_{\mathrm{p}}, \boldsymbol{\xi}_{\mathrm{p}}, \mathbf{v}_{\mathrm{f}}, \boldsymbol{\xi}_{\mathrm{f}})$$

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Computational Models for Polydisperse Particulate and Multiphase Systems

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Generalized Population Balance Equation

NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations

Real-Space



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Advection

NDF for Fluid–Particle Systems

Based on these definitions, how can we derive transport equations for fluid–particle systems?



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Quadrature-**Based Moment** Methods **Closure Problem** Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Eluid\_Particle Systems Moment Transport Equations **Beal-Space** 

Advection

Starting from mesoscale models for particle properties

GPBE for Fluid–Particle Systems

- From this equation we find transport equation for one-particle

$$\begin{split} \frac{\partial n}{\partial t} &+ \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n + \frac{\partial}{\partial \mathbf{v}_{\mathrm{p}}} \cdot \left( \langle \mathbf{A}_{\mathrm{fp}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{p}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{p}}} \cdot \langle \mathbf{G}_{\mathrm{p}} \rangle_{1} n \\ &+ \frac{\partial}{\partial \mathbf{v}_{\mathrm{f}}} \cdot \left( \langle \mathbf{A}_{\mathrm{pf}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{f}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{f}}} \cdot \langle \mathbf{G}_{\mathrm{f}} \rangle_{1} n = \mathcal{S}_{1} \end{split}$$



Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations Real-Space

Advection

 Starting from mesoscale models for particle properties (validated with DNS of fluid–particle system when possible), we first derive generalized transport equation for *f<sub>N<sub>p</sub></sub>* (generalized Liouville equation)

- From this equation we find transport equation for one-particle PDF  $f_1^{(n)}$  by integrating out all degrees of freedom except those associated with  $n^{\text{th}}$  particle (loss of information and generation of unclosed terms)
- Finally, using definition of fluid-particle NDF we derive GPBE:

$$\begin{aligned} \frac{\partial n}{\partial t} &+ \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n + \frac{\partial}{\partial \mathbf{v}_{\mathrm{p}}} \cdot \left( \langle \mathbf{A}_{\mathrm{fp}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{p}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{p}}} \cdot \langle \mathbf{G}_{\mathrm{p}} \rangle_{1} n \\ &+ \frac{\partial}{\partial \mathbf{v}_{\mathrm{f}}} \cdot \left( \langle \mathbf{A}_{\mathrm{pf}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{f}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{f}}} \cdot \langle \mathbf{G}_{\mathrm{f}} \rangle_{1} n = \mathcal{S}_{1} \end{aligned}$$



Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations Real-Space

Advection

- Starting from mesoscale models for particle properties (validated with DNS of fluid–particle system when possible), we first derive generalized transport equation for  $f_{N_p}$  (generalized Liouville equation)
- From this equation we find transport equation for one-particle PDF  $f_1^{(n)}$  by integrating out all degrees of freedom except those associated with  $n^{\text{th}}$  particle (loss of information and generation of unclosed terms)
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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport Equations Real-Space

Advection

- Starting from mesoscale models for particle properties (validated with DNS of fluid–particle system when possible), we first derive generalized transport equation for  $f_{N_p}$  (generalized Liouville equation)
- From this equation we find transport equation for one-particle PDF  $f_1^{(n)}$  by integrating out all degrees of freedom except those associated with  $n^{\text{th}}$  particle (loss of information and generation of unclosed terms)
- Finally, using definition of fluid-particle NDF we derive GPBE:

$$\begin{aligned} \frac{\partial n}{\partial t} &+ \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n + \frac{\partial}{\partial \mathbf{v}_{\mathrm{p}}} \cdot \left( \langle \mathbf{A}_{\mathrm{fp}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{p}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{p}}} \cdot \langle \mathbf{G}_{\mathrm{p}} \rangle_{1} n \\ &+ \frac{\partial}{\partial \mathbf{v}_{\mathrm{f}}} \cdot \left( \langle \mathbf{A}_{\mathrm{pf}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{f}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{f}}} \cdot \langle \mathbf{G}_{\mathrm{f}} \rangle_{1} n = \mathcal{S}_{1} \end{aligned}$$



#### Summary

- We consider only mesoscale models where phase-space fluxes and source terms in GPBE are closed, in other words, depend only on independent variables (t, x,  $v_p$ ,  $\xi_p$ ,  $v_f$ ,  $\xi_f$ ) and on NDF  $n(t, x, v_p, \xi_p, v_f, \xi_f)$
- Finding accurate mesoscale closures is highly non-trivial task (e.g. drag coefficient for dense particulate systems, aggregation integrals and kernels, etc.)
- In order to reduce dimensionality of GPBE it is sometimes possible to work with selected moments of NDF by solving their transport equations
- Let us see how to derive moment equations and what additional problems are generated in their derivation (moment closure problem)

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Computational Models for Polydisperse Particulate and Multiphase Systems

Rodney O. Fox International Francqui Professor

Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Bealizable Moments

Generalized

Population Balance Equation

NDF for Fluid–Particle

Systems

Fluid–Particle Systems



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Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation

Realizable Moments

Population Balance Equation NDF for Fluid–Particle Systems GPBE for

Fluid–Particle Systems Moment Transport

Equations Real-Space Advection



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Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

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. NDF for Fluid–Particle

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- Moment Transport Equations Real-Space Advection

- At this point we will not enter into details of mesoscale models but it is worth mentioning that a set of consistency constraints has to be satisfied
  - Mesoscale models are designed to satisfy consistency constraints (e.g., conservation of mass, species, momentum, energy, etc.)
  - Operation of deriving moment transport equations requires manipulation of multivariate integrals, it is therefore useful to review some integration rules



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# Moment Transport Equations

#### Treatment of time and space derivatives

Let  $\mathit{g}(v_p, \pmb{\xi}_p, v_f, \pmb{\xi}_f)$  be arbitrary function of its variables Then

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$$\begin{aligned} \left(\frac{\partial n}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{p}n\right) g \, \mathrm{d}\mathbf{v}_{p} \, \mathrm{d}\boldsymbol{\xi}_{p} \, \mathrm{d}\mathbf{v}_{f} \, \mathrm{d}\boldsymbol{\xi}_{f} \\ &= \int \left(\frac{\partial gn}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{p}gn\right) \, \mathrm{d}\mathbf{v}_{p} \, \mathrm{d}\boldsymbol{\xi}_{p} \, \mathrm{d}\mathbf{v}_{f} \, \mathrm{d}\boldsymbol{\xi}_{f} \\ &= \frac{\partial}{\partial t} \left(\int gn \, \mathrm{d}\mathbf{v}_{p} \, \mathrm{d}\boldsymbol{\xi}_{p} \, \mathrm{d}\mathbf{v}_{f} \, \mathrm{d}\boldsymbol{\xi}_{f}\right) + \frac{\partial}{\partial \mathbf{x}} \cdot \left(\int \mathbf{v}_{p}gn \, \mathrm{d}\mathbf{v}_{p} \, \mathrm{d}\boldsymbol{\xi}_{p} \, \mathrm{d}\mathbf{v}_{f} \, \mathrm{d}\boldsymbol{\xi}_{f}\right) \\ &= \frac{\partial}{\partial t} \langle g \rangle + \frac{\partial}{\partial \mathbf{x}} \cdot \langle \mathbf{v}_{p}g \rangle \end{aligned}$$

where  $\langle \bullet \rangle$  denotes integral w.r.t. *n* 



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# Moment Transport Equations

#### Treatment of velocity derivatives

With velocity derivatives, it is necessary to use integration by parts:

$$\begin{split} &\int g \frac{\partial}{\partial \mathbf{v}_{p}} \cdot \left( \langle \mathbf{A}_{fp} \rangle_{1} + \langle \mathbf{A}_{p} \rangle_{1} \right) n \, \mathrm{d}\mathbf{v}_{p} \, \mathrm{d}\boldsymbol{\xi}_{p} \, \mathrm{d}\mathbf{v}_{f} \, \mathrm{d}\boldsymbol{\xi}_{f} \\ &= \left( \langle \mathbf{A}_{fp} \rangle_{1} + \langle \mathbf{A}_{p} \rangle_{1} \right) g n \Big|_{\mathbf{v}_{p} = \pm \infty} - \int \left( \langle \mathbf{A}_{fp} \rangle_{1} + \langle \mathbf{A}_{p} \rangle_{1} \right) \cdot \frac{\partial g}{\partial \mathbf{v}_{p}} n \, \mathrm{d}\mathbf{v}_{p} \, \mathrm{d}\boldsymbol{\xi}_{p} \, \mathrm{d}\mathbf{v}_{f} \, \mathrm{d}\boldsymbol{\xi}_{f} \end{split}$$

First term corresponds to flux normal to surface bounding velocity phase space and since velocity space extends to infinity, this flux must be null



Treatment of internal-coordinate derivatives

Also for internal-coordinate derivatives it is necessary to use integration by parts:

$$\int g \frac{\partial}{\partial \xi_{\rm p}} \cdot \langle \mathbf{G}_{\rm p} \rangle_{1} n \, \mathrm{d} \mathbf{v}_{\rm p} \, \mathrm{d} \xi_{\rm p} \, \mathrm{d} \mathbf{v}_{\rm f} \, \mathrm{d} \xi_{\rm f}$$
$$= \langle \mathbf{G}_{\rm p} \rangle_{1} g n \Big|_{\xi_{\rm p} = \max} - \langle \mathbf{G}_{\rm p} \rangle_{1} g n \Big|_{\xi_{\rm p} = \min} - \int \langle \mathbf{G}_{\rm p} \rangle_{1} \cdot \frac{\partial g}{\partial \xi_{\rm p}} n \, \mathrm{d} \mathbf{v}_{\rm p} \, \mathrm{d} \xi_{\rm p} \, \mathrm{d} \mathbf{v}_{\rm f} \, \mathrm{d} \xi_{\rm f}$$

Since for particle internal coordinates phase space does not often extend to infinity, flux normal to phase-space boundaries might not be null (e.g. particle dissolution, droplet evaporation)

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#### **Disperse-Phase Number Transport**

• Total number concentration *N*(*t*, **x**) corresponds to zero-order moment of NDF (i.e., *g* = 1) and is defined by

$$N := \int n \,\mathrm{d}\mathbf{v}_{\mathrm{p}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \,\mathrm{d}\mathbf{v}_{\mathrm{f}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{f}}$$

Its transport equation can be found from GPBE

$$\frac{\partial N}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{U}_{\mathrm{N}} N = S_{\mathrm{N}}$$

Number-average disperse-phase velocity is defined by

$$\mathbf{U}_{\mathrm{N}} := \frac{1}{N} \int \mathbf{v}_{\mathrm{p}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

Particle-number source term by

$$S_{\mathrm{N}} := \int S_{1} \,\mathrm{d}\mathbf{v}_{\mathrm{p}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \,\mathrm{d}\mathbf{v}_{\mathrm{f}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{f}}$$



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#### Disperse-Phase Number Transport

 Total number concentration N(t, x) corresponds to zero-order moment of NDF (i.e., g = 1) and is defined by

$$N := \int n \, \mathrm{d}\mathbf{v}_{\mathrm{p}} \, \mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d}\mathbf{v}_{\mathrm{f}} \, \mathrm{d}\boldsymbol{\xi}_{\mathrm{f}}$$

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Particle-number source term by

$$S_{\mathrm{N}} := \int S_{\mathrm{I}} \, \mathrm{d}\mathbf{v}_{\mathrm{p}} \, \mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d}\mathbf{v}_{\mathrm{f}} \, \mathrm{d}\boldsymbol{\xi}_{\mathrm{f}}$$



#### Disperse-Phase Number Transport

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Real-Space Advection

# Disperse-Phase Volume Transport

 If first internal coordinate ξ<sub>p1</sub> is particle volume (V<sub>p</sub>) disperse-phase volume fraction is defined as (g = ξ<sub>p1</sub> = V<sub>p</sub>):

$$\alpha_{\mathrm{p}} := \int \xi_{\mathrm{pl}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

• Its transport equation can be derived from GPBE:

$$\frac{\partial \alpha_{\rm p}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \alpha_{\rm p} \mathbf{U}_{\rm V} = \llbracket G_{\rm p} \rrbracket_{\rm V} + S_{\rm V}$$

Volume-average disperse-phase velocity is defined by

$$U_{\mathrm{V}} := \frac{1}{\alpha_{\mathrm{p}}} \int \xi_{\mathrm{p}1} \mathbf{v}_{\mathrm{p}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

· Particle-volume source terms are defined by

$$\llbracket G_{\mathbf{p}} \rrbracket_{\mathbf{V}} := \int \langle G_{\mathbf{p}1} \rangle_1 n \, \mathrm{d} \mathbf{v}_{\mathbf{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d} \mathbf{v}_{\mathbf{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{f}}$$

 $S_{\rm V} := \int \xi_{\rm p1} S_1 \, \mathrm{d} \mathbf{v}_{\rm p} \, \mathrm{d} \xi_{\rm p} \, \mathrm{d} \mathbf{v}_{\rm f} \, \mathrm{d} \xi_{\rm f}$ 



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Real-Space Advection  If first internal coordinate ξ<sub>p1</sub> is particle volume (V<sub>p</sub>) disperse-phase volume fraction is defined as (g = ξ<sub>p1</sub> = V<sub>p</sub>):

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Disperse-Phase Volume Transport

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### Disperse-Phase Volume Transport

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$$\alpha_{\mathrm{p}} := \int \xi_{\mathrm{pl}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

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 $S_{\rm V} := \int \xi_{\rm p1} S_1 \, \mathrm{d} \mathbf{v}_{\rm p} \, \mathrm{d} \xi_{\rm p} \, \mathrm{d} \mathbf{v}_{\rm f} \, \mathrm{d} \xi_{\rm f}$ 

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Generalized Population Balance Equation NDF for Fluid-Particle Systems Moment Transport Equations

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$$\alpha_{\mathbf{p}} := \int \xi_{\mathbf{p}1} n \, \mathrm{d} \mathbf{v}_{\mathbf{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d} \mathbf{v}_{\mathbf{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{f}}$$

• Its transport equation can be derived from GPBE:

$$\frac{\partial \alpha_{\rm p}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \alpha_{\rm p} \mathbf{U}_{\rm V} = \llbracket G_{\rm p} \rrbracket_{\rm V} + S_{\rm V}$$

· Volume-average disperse-phase velocity is defined by

$$\mathbf{U}_{\mathrm{V}} := \frac{1}{\alpha_{\mathrm{p}}} \int \xi_{\mathrm{p}1} \mathbf{v}_{\mathrm{p}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

· Particle-volume source terms are defined by

$$\llbracket G_{\mathbf{p}} \rrbracket_{\mathbf{V}} := \int \langle G_{\mathbf{p}1} \rangle_1 n \, \mathrm{d} \mathbf{v}_{\mathbf{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d} \mathbf{v}_{\mathbf{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}}$$

 $S_{\mathrm{V}} := \int \xi_{\mathrm{p}1} S_1 \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \xi_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \xi_{\mathrm{f}}$ 



### Disperse-Phase Volume Transport

Computational Models for Polydisperse Particulate and Multiphase Systems

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Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport

Equations Real-Space Advection  If first internal coordinate ξ<sub>p1</sub> is particle volume (V<sub>p</sub>) disperse-phase volume fraction is defined as (g = ξ<sub>p1</sub> = V<sub>p</sub>):

$$\alpha_{\mathrm{p}} := \int \xi_{\mathrm{pl}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

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$$\llbracket G_{\mathbf{p}} \rrbracket_{\mathbf{V}} := \int \langle G_{\mathbf{p}1} \rangle_{1} n \, \mathrm{d} \mathbf{v}_{\mathbf{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d} \mathbf{v}_{\mathbf{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{f}}$$
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Equations Real-Space Advection

# Fluid-Phase Volume Transport

• If we let internal coordinate  $\xi_{f1}$  be equal to fluid volume seen by particle, fluid-phase volume fraction is

$$\alpha_{\rm f} := \int \xi_{\rm fl} n \, \mathrm{d} \mathbf{v}_{\rm p} \, \mathrm{d} \boldsymbol{\xi}_{\rm p} \, \mathrm{d} \mathbf{v}_{\rm f} \, \mathrm{d} \boldsymbol{\xi}_{\rm f}$$

• Volume-average fluid velocity is

$$\mathbf{U}_{\mathrm{fV}} := \frac{1}{\alpha_{\mathrm{f}}} \int \boldsymbol{\xi}_{\mathrm{f1}} \mathbf{v}_{\mathrm{f}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

• Transport equation for  $\alpha_{\rm f}$  is

$$\frac{\partial \alpha_{\rm f}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \alpha_{\rm f} \mathbf{U}_{\rm pV} = \llbracket G_{\rm f} \rrbracket_{\rm V} + S_{\rm fV}$$

where

$$\mathbf{U}_{\mathrm{pV}} := \frac{1}{\alpha_{\mathrm{f}}} \int \xi_{\mathrm{fl}} \mathbf{v}_{\mathrm{p}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}}$$

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Fluid-Phase Volume Transport

$$\mathbf{U}_{\mathrm{fV}} := \frac{1}{\alpha_{\mathrm{f}}} \int \boldsymbol{\xi}_{\mathrm{f1}} \mathbf{v}_{\mathrm{f}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

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where

$$\mathbf{U}_{\mathrm{pV}} := \frac{1}{\alpha_{\mathrm{f}}} \int \xi_{\mathrm{fl}} \mathbf{v}_{\mathrm{p}} n \,\mathrm{d}\mathbf{v}_{\mathrm{p}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \,\mathrm{d}\mathbf{v}_{\mathrm{f}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}}$$

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Equations Real-Space Advection • By definition,  $\alpha_p + \alpha_f = 1$  and, in the absence of mass transfer between phases:

$$\frac{\partial \alpha_{\rm f}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \alpha_{\rm f} \mathbf{U}_{\rm fV} = 0$$

• This simply states that fluid-phase volume fraction is conserved quantity and therefore we must have:

$$\llbracket G_{\rm f} \rrbracket_{\rm V} = \frac{\partial}{\partial \mathbf{x}} \cdot \alpha_{\rm f} \left( \mathbf{U}_{\rm pV} - \mathbf{U}_{\rm fV} \right)$$

 In case of no mass transfer it will be necessary for (G<sub>f1</sub>)<sub>1</sub> to be nonzero: volume of fluid seen by a particle must change along a particle trajectory due to presence of other particles!

$$\langle G_{\rm f1} \rangle_1 = \frac{1}{n} \frac{\partial}{\partial \mathbf{x}} \cdot (\mathbf{v}_{\rm p} - \mathbf{v}_{\rm f}) \xi_{\rm f1} n$$



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Real-Space Advection

# **Disperse-Phase Mass Transport**

- If disperse phase has particles with different volumes and different masses (or material densities), at least two internal coordinates are necessary
- First internal coordinate particle volume and second particle mass (ξ<sub>p2</sub> := M<sub>p</sub> = ρ<sub>p</sub>V<sub>p</sub>; ρ<sub>p</sub> is material density)
  - Disperse-phase mass density is defined by

$$\varrho_{\mathrm{p}} := \int \xi_{\mathrm{p}2} n \,\mathrm{d}\mathbf{v}_{\mathrm{p}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \,\mathrm{d}\mathbf{v}_{\mathrm{f}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{f}}$$

• Its transport equation is derived from GPBE ( $g = \xi_{p2} = M_p$ )

$$\frac{\partial \varrho_{\rm p}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\rm p} \mathbf{U}_{\rm M} = \llbracket G_{\rm p} \rrbracket + \mathcal{S}_{\rm M}$$

Mass-average disperse-phase velocity

$$\mathbf{U}_{\mathrm{M}} := \frac{1}{\varrho_{\mathrm{p}}} \int \xi_{\mathrm{p}2} \mathbf{v}_{\mathrm{p}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}$$



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Real-Space Advection

# **Disperse-Phase Mass Transport**

• Since total mass of fluid–particle system is conserved, we can define fluid-phase mass density  $\varrho_{\rm f}$  by

$$\frac{\partial \varrho_{\rm f}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\rm f} \mathbf{U}_{\rm f} = -\llbracket G_{\rm p} \rrbracket - \mathcal{S}_{\rm M}$$

- $\rho_p$  and  $\rho_f$  are not actual material densities  $\rho_p$  and  $\rho_f$ , they are equal to mass of solid (fluid) per unit volume of fluid–particle system
- Similarly we can define mixture mass density 
   *ρ*<sub>mix</sub> := *ρ*<sub>p</sub> + *ρ*<sub>f</sub>, that satisfies mixture continuity equation:

$$\frac{\partial \varrho_{\mathsf{mix}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\mathsf{mix}} \mathbf{U}_{\mathsf{mix}} = \mathbf{0}$$

Mass-average mixture velocity is defined by

$$\mathbf{U}_{\mathsf{mix}} := \frac{1}{\varrho_{\mathsf{mix}}} \left( \varrho_{\mathrm{p}} \mathbf{U}_{\mathrm{p}} + \varrho_{\mathrm{f}} \mathbf{U}_{\mathrm{f}} \right)$$

Transport equations for 
 *Q*<sub>p</sub> and 
 *Q*<sub>f</sub> are used in two-fluid models and follow directly from GPBE

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Mass-average mixture velocity is defined by

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Advection

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$$\mathbf{U}_{\mathsf{mix}} := \frac{1}{\varrho_{\mathsf{mix}}} \left( \varrho_{\mathrm{p}} \mathbf{U}_{\mathrm{p}} + \varrho_{\mathrm{f}} \mathbf{U}_{\mathrm{f}} \right)$$

Transport equations for 
 *Q*<sub>p</sub> and 
 *Q*<sub>f</sub> are used in two-fluid models and follow directly from GPBE

Rodney O. Fox International Francqui Professor



Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport

Equations Real-Space Advection • Since total mass of fluid–particle system is conserved, we can define fluid-phase mass density  $\varrho_f$  by

$$\frac{\partial \varrho_{\rm f}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\rm f} \mathbf{U}_{\rm f} = -\llbracket G_{\rm p} \rrbracket - \mathcal{S}_{\rm M}$$

- $\rho_p$  and  $\rho_f$  are not actual material densities  $\rho_p$  and  $\rho_f$ , they are equal to mass of solid (fluid) per unit volume of fluid–particle system
- Similarly we can define mixture mass density  $\rho_{mix} := \rho_p + \rho_f$ , that satisfies mixture continuity equation:

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Moment Transport Equations Real-Space Advection

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Computational Models for Polydisperse Particulate and Multiphase Systems

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Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

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Models for Polydisperse Particulate and Multiphase Systems

Computational

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Moment Transport Equations Beal-Space

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Generalized Population Balance Equation NDF for Fluid-Particle Systems Moment Transport Equations

Real-Space Advection

# Disperse-Phase Momentum Transport

Disperse-phase momentum density is defined by

$$\varrho_{\mathrm{p}}\mathbf{U}_{\mathrm{M}} := \int \xi_{\mathrm{p}2} \mathbf{v}_{\mathrm{p}} n \,\mathrm{d}\mathbf{v}_{\mathrm{p}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}} \,\mathrm{d}\mathbf{v}_{\mathrm{f}} \,\mathrm{d}\boldsymbol{\xi}_{\mathrm{f}}$$

where  $\xi_{p2} = M_p$  corresponds to particle mass

• As usual its transport equation is derived from GPBE ( $g = \xi_{p2} \mathbf{v}_{p}$ ):

$$\frac{\partial \varrho_{\mathbf{p}} \mathbf{U}_{\mathbf{M}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\mathbf{p}} \mathbf{F}_{\mathbf{p}} = \varrho_{\mathbf{p}} [\![\mathbf{A}_{\mathbf{fp}}]\!]_{\mathbf{p}} + \varrho_{\mathbf{p}} [\![\mathbf{A}_{\mathbf{p}}]\!]_{\mathbf{p}} + [\![\mathbf{G}_{\mathbf{p}}]\!]_{\mathbf{p}} + \varrho_{\mathbf{p}} [\![\mathbf{S}]\!]_{\mathbf{p}}$$

where (unclosed) momentum-convection term (second-order tensor) is defined by

$$\varrho_{\mathbf{p}}\mathbf{F}_{\mathbf{p}} := \int \xi_{\mathbf{p}2}(\mathbf{v}_{\mathbf{p}} \otimes \mathbf{v}_{\mathbf{p}}) n \, \mathrm{d}\mathbf{v}_{\mathbf{p}} \, \mathrm{d}\boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d}\mathbf{v}_{\mathbf{f}} \, \mathrm{d}\boldsymbol{\xi}_{\mathbf{f}}$$



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# Disperse-Phase Momentum Transport

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### where $\xi_{p2} = M_p$ corresponds to particle mass

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

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Moment Transport Equations Real-Space Advection Disperse-Phase Momentum Transport

• Surface forces on particles due to surrounding fluid (e.g., drag, lift, and pressure forces)

$$\varrho_{\mathbf{p}} \llbracket \mathbf{A}_{\mathrm{fp}} \rrbracket_{\mathbf{p}} := \int \xi_{\mathbf{p}2} \langle \mathbf{A}_{\mathrm{fp}2} \rangle_1 n \, \mathrm{d} \mathbf{v}_{\mathbf{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathbf{p}}$$

• Body forces (such as gravity):

$$\varrho_{\mathbf{p}}[\![\mathbf{A}_{\mathbf{p}}]\!]_{\mathbf{p}} := \int \xi_{\mathbf{p}2} \langle \mathbf{A}_{\mathbf{p}2} \rangle_{1} n \, d\mathbf{v}_{\mathbf{p}} \, d\boldsymbol{\xi}_{\mathbf{p}} \, d\mathbf{v}_{\mathbf{f}} \, d\boldsymbol{\xi}_{\mathbf{f}}$$

Momentum added to particle phase due to mass transfer from liquid

$$[\mathbf{G}_{\mathbf{p}}]]_{\mathbf{p}} := \int \mathbf{v}_{\mathbf{p}} \langle G_{\mathbf{p}2} \rangle_1 n \, \mathrm{d}\mathbf{v}_{\mathbf{p}} \, \mathrm{d}\boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d}\mathbf{v}_{\mathbf{f}} \, \mathrm{d}\boldsymbol{\xi}_{\mathbf{f}}$$

• Discontinuous changes in particle momentum due to collisions and particle nucleation:

$$\varrho_{\mathbf{p}}[[\mathbf{S}]]_{\mathbf{p}} := \int \xi_{\mathbf{p}2} \mathbf{v}_{\mathbf{p}} \mathcal{S}_{1} \, \mathrm{d}\mathbf{v}_{\mathbf{p}} \, \mathrm{d}\boldsymbol{\xi}_{\mathbf{p}} \, \mathrm{d}\mathbf{v}_{\mathbf{f}} \, \mathrm{d}\boldsymbol{\xi}_{\mathbf{f}}$$



Computational Models for Polydisperse Particulate and Multiphase Systems

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Generalized Population

Balance Equation

Fluid–Particle Systems

GPBE for Fluid–Particle Systems

Moment Transport Equations

Real-Space Advection

#### Constant (and equal) volume and mass

• For monodisperse particles, disperse-phase mass density is  $\rho_{\rm p} = \rho_{\rm p} \alpha_{\rm p}$ , mass average can be replaced by number average, and transport equation for disperse-phase momentum density is

$$\frac{\partial \rho_{p} \alpha_{p} \mathbf{U}_{p}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \rho_{p} \alpha_{p} \mathbf{U}_{p} \otimes \mathbf{U}_{p} + \frac{\partial}{\partial \mathbf{x}} \cdot \rho_{p} \alpha_{p} \llbracket \mathbf{u}_{p} \mathbf{u}_{p} \rrbracket_{N} = \rho_{p} \alpha_{p} \llbracket \mathbf{A}_{fp} \rrbracket_{N} + \rho_{p} \alpha_{p} \llbracket \mathbf{A}_{p} \rrbracket_{N} + \rho_{p} \alpha_{p} \varrho_{p} \llbracket \mathbf{S} \rrbracket$$

- Disperse-phase pressure tensor,  $[\![u_pu_p]\!]_N=F_N-U_p\otimes U_p,$  is central second-order moment
- Term for collisions can also generate separate spatial flux term (collisional flux) which is added to disperse-phase pressure tensor



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Computational Models for Polydisperse Particulate and Multiphase Systems

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Population Balance Equation NDF for Eluid-Particle

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NDF for

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### Towards the Two-Fluid Model

Constant (and equal) volume and mass

• For monodisperse particles, disperse-phase mass density is  $\rho_{\rm p} = \rho_{\rm p} \alpha_{\rm p}$ , mass average can be replaced by number average, and transport equation for disperse-phase momentum density is

$$\frac{\partial \rho_{\mathbf{p}} \alpha_{\mathbf{p}} \mathbf{U}_{\mathbf{p}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \rho_{\mathbf{p}} \alpha_{\mathbf{p}} \mathbf{U}_{\mathbf{p}} \otimes \mathbf{U}_{\mathbf{p}} + \frac{\partial}{\partial \mathbf{x}} \cdot \rho_{\mathbf{p}} \alpha_{\mathbf{p}} [\![\mathbf{u}_{\mathbf{p}} \mathbf{u}_{\mathbf{p}}]\!]_{\mathbf{N}} = \rho_{\mathbf{p}} \alpha_{\mathbf{p}} [\![\mathbf{A}_{\mathbf{fp}}]\!]_{\mathbf{N}} + \rho_{\mathbf{p}} \alpha_{\mathbf{p}} [\![\mathbf{A}_{\mathbf{fp}}]\!]_{\mathbf{N}} + \rho_{\mathbf{p}} \alpha_{\mathbf{p}} \varrho_{\mathbf{p}} [\![\mathbf{S}]\!]_{\mathbf{N}}$$

- Disperse-phase pressure tensor,  $[\![u_pu_p]\!]_N=F_N-U_p\otimes U_p,$  is central second-order moment
- Term for collisions can also generate separate spatial flux term (collisional flux) which is added to disperse-phase pressure tensor

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Computational Models for Polydisperse Particulate and Multiphase Systems

Rodney O. Fox International Francqui Professor

Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems

Moment Transport Equations Real-Space



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Generalized

Population Balance Equation NDF for Fluid–Particle Systems GPBE for Fluid–Particle Systems

Moment Transport Equations Real-Space

Real-Space Advection

## Towards the Two-Fluid Model

#### Constant (and equal) volume and mass

 From GPBE we can also derive a transport equation for fluid-phase momentum density (after applying constraints)

$$\frac{\partial \varrho_{f} \mathbf{U}_{f}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{f} \llbracket \mathbf{U}_{f} \otimes \mathbf{U}_{f} \rrbracket_{f} = \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{S}_{f} + \varrho_{f} \mathbf{A}_{f} - \varrho_{p} \llbracket \mathbf{A}_{fp} \rrbracket_{p} - \llbracket \mathbf{G}_{p} \rrbracket_{p} - \varrho_{p} \llbracket \mathbf{S} \rrbracket_{p}$$

- ${\bf S}_{\rm f}$  and  ${\bf A}_{\rm f}$  denote the viscous/pressure stress tensor and body forces acting on fluid phase
- Convection term

$$\llbracket \mathbf{U}_{\mathrm{f}} \otimes \mathbf{U}_{\mathrm{f}} \rrbracket_{\mathrm{f}} := \int \xi_{\mathrm{f}1} \mathbf{v}_{\mathrm{f}} \otimes \mathbf{v}_{\mathrm{f}} n \, \mathrm{d} \mathbf{v}_{\mathrm{p}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{p}} \, \mathrm{d} \mathbf{v}_{\mathrm{f}} \, \mathrm{d} \boldsymbol{\xi}_{\mathrm{f}}$$

#### requires separate model for microscale (pseudo) turbulence



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Generalized Population

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Advection

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### Mixture Model

Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population Balance

Equation NDF for Fluid–Particle Systems GPBE for Fluid–Particle Systems

Moment Transport Equations Real-Space Advection Recalling definition of mixture mass density, *ρ*<sub>mix</sub> ≡ *ρ*<sub>p</sub> + *ρ*<sub>f</sub> whose transport equation is:

$$\frac{\partial \varrho_{\mathsf{mix}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\mathsf{mix}} \mathbf{U}_{\mathsf{mix}} = 0$$

and  $\mathbf{U}_{\text{mix}} := \frac{1}{\rho_{\text{mix}}} \left( \rho_{p} \mathbf{U}_{p} + \rho_{f} \mathbf{U}_{f} \right)$  is mass-average mixture velocity

- We can derive (by summing up equations for  $\mathbf{U}_p$  and  $\mathbf{U}_f)$ :

$$\frac{\partial \varrho_{\mathsf{mix}} \mathbf{U}_{\mathsf{mix}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \left( \varrho_{\mathsf{p}} \mathbf{F}_{\mathsf{p}} + \varrho_{\mathsf{f}} \llbracket \mathbf{U}_{\mathsf{f}} \otimes \mathbf{U}_{\mathsf{f}} \rrbracket_{\mathsf{f}} \right) = \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{S}_{\mathsf{f}} + \varrho_{\mathsf{p}} \llbracket \mathbf{A}_{\mathsf{p}} \rrbracket_{\mathsf{p}} + \varrho_{\mathsf{f}} \mathbf{A}_{\mathsf{f}}$$

 This expression does not contain terms for momentum transfer between phases but can be solved only when U<sub>mix</sub> is very close to U<sub>f</sub> (i.e., very small Stokes numbers)



Computational Models for Polydisperse

Particulate and Multiphase Systems

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Methods Closure Problem

Computing Quadrature Approximation Realizable Moments Generalized Population Balance Equation NDF for

Fluid–Particle Systems GPBE for Fluid–Particle Systems Moment Transport Equations Real-Space Advection

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Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized

Population Balance Equation NDF for Fluid–Particle Systems GPBE for Fluid–Particle Systems

Moment Transport Equations Real-Space Advection



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Computational Models for Polydisperse Particulate and Multiphase Systems

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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Baalizable Moments

Generalized Population

Balance Equation NDF for Fluid–Particle Systems GPBE for Fluid–Particle Systems

Moment Transport Equations Real-Space Advection



#### Summary

- Through ensemble average and by using some simplifying hypotheses NDF for multiphase system has been defined
- NDF completely defines multiphase system
- Moments of NDF correspond to relevant measurable properties: disperse-phase number concentration, disperse- and fluid-phase volume fractions and mass densities, mixture mass density, number-, volume- and mass-average velocities for disperse and fluid phases and mass-average mixture velocity
- Evolution of NDF is dictated by GPBE and from it, transport equations for moments can be derived simply by applying moment transform
- Two-fluid model and mixture model are directly derivable from moment transport equations with additional hypothesis of constant and equal particle mass and volume

Computational Models for Polydisperse Particulate and Multiphase Systems

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Systems



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Equations Real-Space

- In general moment transport equations are not closed, as terms appearing in them cannot be written in terms of moments themselves
  - In all these cases NDF has to be reconstructed
  - **Parameterized NDF:** functional form for NDF in terms of a few lower-order moments (e.g. single Dirac delta function, log-normal distribution)
  - Functional expansion for NDF: similar to previous one but in order to increase number of degrees of freedom in systematic manner functional expansion can be used to represent NDF
  - **Discrete NDF:** discrete form for phase-space variables, discretized on grid (e.g. uniform, geometric series, etc.)
  - Quadrature-based moment methods: reconstruction of NDF using sum of Dirac delta functions located at nodes of quadrature approximation (i.e. zeros of orthogonal polynomials)



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Advection

• Real-space advection (second term on LHS

$$\begin{split} \frac{\partial n}{\partial t} &+ \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n + \frac{\partial}{\partial \mathbf{v}_{\mathrm{p}}} \cdot \left( \langle \mathbf{A}_{\mathrm{fp}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{p}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{p}}} \cdot \langle \mathbf{G}_{\mathrm{p}} \rangle_{1} n \\ &+ \frac{\partial}{\partial \mathbf{v}_{\mathrm{f}}} \cdot \left( \langle \mathbf{A}_{\mathrm{pf}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{f}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{f}}} \cdot \langle \mathbf{G}_{\mathrm{f}} \rangle_{1} n = \mathcal{S}_{1} \end{split}$$

• It represents the movement of particles in real space:

$$\frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n = \frac{\partial}{\partial x_{1}} v_{\mathrm{p}1} n + \frac{\partial}{\partial x_{2}} v_{\mathrm{p}2} n + \frac{\partial}{\partial x_{3}} v_{\mathrm{p}3} n$$

- Particle velocity plays an important role since it generates spatial transport: **active variable**
- Other internal coordinates (e.g. particle size) are **passive variables**: carried along with given velocity



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Advection

Real-space advection (second term on LHS)

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$$\frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n = \frac{\partial}{\partial x_{1}} v_{\mathrm{p1}} n + \frac{\partial}{\partial x_{2}} v_{\mathrm{p2}} n + \frac{\partial}{\partial x_{3}} v_{\mathrm{p3}} n$$

- Particle velocity plays an important role since it generates spatial transport: **active variable**
- Other internal coordinates (e.g. particle size) are **passive variables**: carried along with given velocity



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Real-space advection (second term on LHS)

$$\begin{split} \frac{\partial n}{\partial t} &+ \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n + \frac{\partial}{\partial \mathbf{v}_{\mathrm{p}}} \cdot \left( \langle \mathbf{A}_{\mathrm{fp}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{p}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{p}}} \cdot \langle \mathbf{G}_{\mathrm{p}} \rangle_{1} n \\ &+ \frac{\partial}{\partial \mathbf{v}_{\mathrm{f}}} \cdot \left( \langle \mathbf{A}_{\mathrm{pf}} \rangle_{1} + \langle \mathbf{A}_{\mathrm{f}} \rangle_{1} \right) n + \frac{\partial}{\partial \boldsymbol{\xi}_{\mathrm{f}}} \cdot \langle \mathbf{G}_{\mathrm{f}} \rangle_{1} n = \mathcal{S}_{1} \end{split}$$

• It represents the movement of particles in real space:

$$\frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{v}_{\mathrm{p}} n = \frac{\partial}{\partial x_1} v_{\mathrm{p}1} n + \frac{\partial}{\partial x_2} v_{\mathrm{p}2} n + \frac{\partial}{\partial x_3} v_{\mathrm{p}3} n$$

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 One strategy that facilitates implementation in CFD codes is to integrate NDF with respect to particle velocity (and to assume that phase-space variables for fluid are slaved to their average values: monokinetic fluid limit):

$$n^*(t, \mathbf{x}, \boldsymbol{\xi}_p) := \int n(t, \mathbf{x}, \mathbf{v}_p, \boldsymbol{\xi}_p) \boldsymbol{\delta}(\mathbf{v}_f - \mathbf{U}_f) \boldsymbol{\delta}(\boldsymbol{\xi}_f - \boldsymbol{\phi}_f) \, \mathrm{d}\mathbf{v}_p \, \mathrm{d}\mathbf{v}_f \, \mathrm{d}\boldsymbol{\xi}_f$$

• An expression for the real-space advection term is obtained:

$$\frac{\partial}{\partial \mathbf{x}} \cdot \langle \mathbf{U}_{\mathbf{p}} | \boldsymbol{\xi}_{\mathbf{p}} \rangle n^* = \frac{\partial}{\partial x_1} \langle U_{\mathbf{p}1} | \boldsymbol{\xi}_{\mathbf{p}} \rangle n^* + \frac{\partial}{\partial x_2} \langle U_{\mathbf{p}2} | \boldsymbol{\xi}_{\mathbf{p}} \rangle n^* + \frac{\partial}{\partial x_3} \langle U_{\mathbf{p}3} | \boldsymbol{\xi}_{\mathbf{p}} \rangle n^*$$

• By definition, conditional particle-phase velocity is

$$\langle \mathbf{U}_{\mathbf{p}} | \boldsymbol{\xi}_{\mathbf{p}} \rangle := \frac{\int \mathbf{v}_{\mathbf{p}} n \, \mathrm{d} \mathbf{v}_{\mathbf{p}}}{\int n \, \mathrm{d} \mathbf{v}_{\mathbf{p}}} = \frac{1}{n^*} \left( \int v_{\mathbf{p}1} n \, \mathrm{d} \mathbf{v}_{\mathbf{p}}, \int v_{\mathbf{p}2} n \, \mathrm{d} \mathbf{v}_{\mathbf{p}}, \int v_{\mathbf{p}3} n \, \mathrm{d} \mathbf{v}_{\mathbf{p}} \right)$$

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# Real-Space Advection and Integration in CFD Codes

 One strategy that facilitates implementation in CFD codes is to integrate NDF with respect to particle velocity (and to assume that phase-space variables for fluid are slaved to their average values: monokinetic fluid limit):

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 $\label{eq:conditioned particle-phase velocity} $\langle \mathbf{U}_p | \boldsymbol{\xi}_p \rangle$ can be determined (in an Eulerian framework) with different approaches:$ 

- **pseudo-homogeneous or dusty gas model**: particles move with velocity of continuous phase  $(St_p \rightarrow 0)$  including (for submicron particles) or neglecting (with larger particles) Brownian diffusion
- equilibrium or algebraic Eulerian model: particles move with velocity calculated from algebraic expression ( $0 < St_p < 0.1$ )
- Eulerian two-fluid model: particles move with velocity calculated with differential equation  $(St_p > 0.1)$

Choice depends on particle Stokes number (ratio between particle and fluid relaxation time scales):

$$\mathrm{St}_{\mathrm{p}} = \frac{\rho_{\mathrm{p}} d_{\mathrm{p}}^2}{18\rho_{\mathrm{f}} \nu_{\mathrm{f}} \tau_{\mathrm{f}}}$$



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#### Pseudo-homogeneous or dusty gas model:

- There is one particle velocity field, identical to fluid velocity
- Preferential accumulation and segregation are not predicted as particles are transported as scalars in continuous phase
- If system is very dilute (one-way coupling), properties of continuous phase (i.e., density and viscosity) are assumed to be equal to those of fluid
- If particle concentration starts to influence fluid phase (two-way coupling), a modified density and viscosity for continuous phase are generally introduced → mixture
- Depending on size of particles Brownian motion may have to be included



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# Real-Space Advection and Integration in CFD Codes

### Equilibrium or algebraic Eulerian model:

• Considering only drag and gravity:

$$\langle \mathbf{U}_{\mathrm{p}} | \boldsymbol{\xi}_{\mathrm{p}} \rangle = \mathbf{U}_{\mathrm{f}} + \left( \frac{\mathsf{D}\mathbf{U}_{\mathrm{f}}}{\mathsf{D}t} - \mathbf{g} \right) \tau_{\mathrm{p}}(\boldsymbol{\xi}_{\mathrm{p}}) + O\left(\tau_{\mathrm{p}}^{2}\right)$$

- One-way coupling (dilute systems): momentum balance equation for continuous phase and algebraic equation for different particle classes: U<sub>pk</sub> := (U<sub>p</sub>|ξ<sub>p</sub> = ξ<sub>pk</sub>) with k = 1,...,N
- Denser particulate systems (two- or three-way coupling): momentum balance equation for mixture
- Moderately dense particulate systems are generally not well described due to importance of particle-particle collisions and particle trajectory crossing

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# Real-Space Advection and Integration in CFD Codes

### Eulerian two-fluid model:

• When particle Stokes number is not small particle velocity must be calculated from disperse-phase momentum equation:

$$\begin{split} \frac{\partial \varrho_{\mathbf{p}} \mathbf{U}_{\mathbf{p}}}{\partial t} + \boldsymbol{\nabla} \cdot \varrho_{\mathbf{p}} \mathbf{U}_{\mathbf{p}} \otimes \mathbf{U}_{\mathbf{p}} &= -\alpha_{\mathbf{p}} \boldsymbol{\nabla} \rho_{\mathbf{f}} + \varrho_{\mathbf{p}} \mathbf{g} + \frac{\varrho_{\mathbf{p}} \rho_{\mathbf{f}} C_{\mathbf{D}} A_{\mathbf{d}}}{2 \gamma \rho_{\mathbf{p}}} |\mathbf{U}_{\mathbf{f}} - \mathbf{U}_{\mathbf{p}}| (\mathbf{U}_{\mathbf{f}} - \mathbf{U}_{\mathbf{p}}) \\ &+ \frac{\varrho_{\mathbf{p}} C_{\mathsf{vm}} \rho_{\mathbf{f}}}{\gamma \rho_{\mathbf{p}}} (\mathbf{U}_{\mathbf{f}} - \mathbf{U}_{\mathbf{p}}) \cdot \boldsymbol{\nabla} \mathbf{U}_{\mathbf{f}} + \frac{\varrho_{\mathbf{p}} C_{\mathbf{L}} \rho_{\mathbf{f}}}{\gamma \rho_{\mathbf{p}}} (\mathbf{U}_{\mathbf{f}} - \mathbf{U}_{\mathbf{p}}) \times (\boldsymbol{\nabla} \times \mathbf{U}_{\mathbf{f}}) \end{split}$$

Likewise, fluid-phase momentum balance is

$$\begin{split} \frac{\partial \varrho_{\rm f} \mathbf{U}_{\rm f}}{\partial t} + \boldsymbol{\nabla} \cdot \varrho_{\rm f} \mathbf{U}_{\rm f} \otimes \mathbf{U}_{\rm f} &= \boldsymbol{\nabla} \cdot \boldsymbol{\tau}_{\rm f} - \alpha_{\rm f} \boldsymbol{\nabla} \rho_{\rm f} + \varrho_{\rm f} \mathbf{g} + \frac{\varrho_{\rm p} \rho_{\rm f} C_{\rm L} A_{\rm d}}{2 \gamma \rho_{\rm p}} |\mathbf{U}_{\rm f} - \mathbf{U}_{\rm p}| (\mathbf{U}_{\rm p} - \mathbf{U}_{\rm f}) \\ &+ \frac{\varrho_{\rm p} C_{\sf wm} \rho_{\rm f}}{\gamma \rho_{\rm p}} (\mathbf{U}_{\rm p} - \mathbf{U}_{\rm f}) \cdot \boldsymbol{\nabla} \mathbf{U}_{\rm f} + \frac{\varrho_{\rm p} C_{\rm L} \rho_{\rm f}}{\gamma \rho_{\rm p}} (\mathbf{U}_{\rm p} - \mathbf{U}_{\rm f}) \times (\boldsymbol{\nabla} \times \mathbf{U}_{\rm f}) \end{split}$$

Approach can be extended to different particle classes,
 U<sub>pk</sub> := ⟨U<sub>p</sub>|ξ<sub>p</sub> = ξ<sub>pk</sub>⟩ with k = 1,...,N, by solving multiple momentum balance equations: multi-fluid model

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# Guidelines for Real-Space Advection

There are three key parameters: particle loading,  $\rho_p/\rho_f$ , particle Stokes number, St, and polydispersity, PDI

- Diffusion equation: sub-micron particles subject to Brownian motion
- Pseudo-homogeneous or dusty-gas model: very small particle Stokes number and limited polydispersity (mom. bal. eq. for cont. phase if system is dilute or mixture otherwise)
- Equilibrium or algebraic Eulerian model with single conditional velocity based on mean particle size: small particle Stokes number and limited polydispersity (mom. bal. eq. ...)
- Q Equilibrium or algebraic Eulerian model with conditional velocities: small particle Stokes number and non-negligible polydispersity (mom. bal. eq. ...)
- Eulerian two-fluid model with particle-phase velocity based on mean particle size: small particle Stokes number and limited polydispersity (in both dilute and dense systems)
- **Eulerian multi-fluid model:** small particle Stokes number and large polydispersity (in both dilute and dense systems)



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- Eulerian two-fluid model with particle-phase velocity based on mean particle size: small particle Stokes number and limited polydispersity (in both dilute and dense systems)
- **Eulerian multi-fluid model:** small particle Stokes number and large polydispersity (in both dilute and dense systems)



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Quadrature-Based Moment Methods Closure Problem Computing Quadrature Approximation Realizable Moments

Generalized Population

Balance Equation NDF for Fluid-Particle Systems GPBE for Fluid-Particle Systems Moment Transport

Equations

Real-Space Advection

### Guidelines for Real-Space Advection

There are three key parameters: particle loading,  $\rho_p/\rho_f$ , particle Stokes number, St, and polydispersity, PDI

- **1** Diffusion equation: sub-micron particles subject to Brownian motion
- Pseudo-homogeneous or dusty-gas model: very small particle Stokes number and limited polydispersity (mom. bal. eq. for cont. phase if system is dilute or mixture otherwise)
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### Part 3

Computational Models for Polydisperse Particulate and Multiphase Systems

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Mesoscale Models for Physical and Chemical Processes

Formulation

Zero-Order Point Processes

First-Order Point Processes

Second-Order Point Processes

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# MESOSCALE MODELS FOR PHYSICAL AND CHEMICAL PROCESSES

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- Conditional phase-space velocities and discontinuous "source" term need mesoscale closures: averaged models for microscale chemical and physical processes
- Simplest procedure is to derive them from single-particle statistics by assuming that all particles are statistically identical and interacting with mean-field quantities which model effects of all other particles
- Effect of multi-particle statistics on phase-space velocities is generally introduced in form of corrections, based for example on disperse-phase volume fraction, that will reduce to isolated-particle statistics in dilute limit
- We will discuss in particular mesoscale models for continuous processes due to fluid–particle momentum transfer ( $\langle A_{fp} \rangle_1$ ), heat and mass transfer ( $\langle G_p \rangle_1$ ) and discontinuous jumps (or point processes) contained in the source term  $S_1$  (zero-, first- and second-order processes)



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### Mesoscale Model for Momentum Transfer

Buoyancy and drag forces  $(A_D/V_p = 3/(2d_p))$  for spheres)

$$\langle \mathbf{A}_{\rm fp} \rangle_1 = -\frac{1}{\rho_{\rm p}} \frac{\partial p_{\rm f}}{\partial \mathbf{x}} + \frac{C_{\rm D}}{2} \frac{A_{\rm D}}{V_{\rm p}} \frac{\rho_{\rm f}}{\rho_{\rm p}} |\mathbf{U}_{\rm f} - \mathbf{U}_{\rm p}| (\mathbf{U}_{\rm f} - \mathbf{U}_{\rm p})$$

• Drag model of Schiller and Nauman ( $Re_p = |U_f - U_p|d_p/v_f$ ):

$$C_{\rm D} = \begin{cases} \frac{24}{{\sf Re}_{\rm p}} \left(1 + 0.15 {\sf Re}_{\rm p}^{0.687}\right) & \text{for } {\sf Re}_{\rm p} \le 1000 \\ 0.445 & \text{for } {\sf Re}_{\rm p} > 1000 \end{cases}$$

Drag Cunningham correction factor for rarefied fluid phase:

$$\frac{C_{\rm D}^*}{C_{\rm D}} = \frac{1}{1 + {\rm Kn} \left[ 2.49 + 0.84 \exp \left( -\frac{1.74}{{\rm Kn}} \right) \right]}$$

• Drag model of Wen and Yu ( $\beta = 3.65$ ):

$$C_{\rm D} = \frac{24}{{\rm Re}_{\rm p}} \left[ 1 + 0.15 (\alpha_{\rm f} {\rm Re}_{\rm p})^{0.687} \right] \alpha_{\rm f}^{-\beta}$$



### Mesoscale Model for Momentum Transfer

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### Buoyancy and drag forces (Eo = $g\Delta\rho d_{\rm p}/\sigma$ )

• Drag model by Tomiyama for pure fluid-fluid systems:

$$C_{\rm D} = \max\left\{\min\left[\frac{16}{\mathsf{Re}_{\rm p}}(1+0.15\mathsf{Re}_{\rm p}^{0.687}), \frac{48}{\mathsf{Re}_{\rm p}}\right], \frac{8}{3}\left(\frac{\mathrm{Eo}}{\mathrm{Eo}+4}\right)\right\}$$

Slightly contaminated systems:

$$C_{\rm D} = \max\left\{\min\left[\frac{24}{\mathsf{Re}_{\rm p}}(1+0.15\mathsf{Re}_{\rm p}^{0.687}), \frac{72}{\mathsf{Re}_{\rm p}}\right], \frac{8}{3}\left(\frac{\mathrm{Eo}}{\mathrm{Eo}+4}\right)\right\}$$

· Fully contaminated systems:

$$C_{\rm D} = \max\left[\frac{24}{{\sf Re}_{\rm p}}(1+0.15{\sf Re}_{\rm p}^{0.687}), \frac{8}{3}\left(\frac{{\rm Eo}}{{\rm Eo}+4}\right)\right]$$



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### Mesoscale Model for Momentum Transfer

 Drag model by Buffo (for contaminated systems) with correction to account for bubble-swarm effect:

$$C_D = (1 - \alpha_g)^{C_1} \max\left[\frac{24}{\mathsf{Re}_{\rm eff}} \left(1 + 0.15\mathsf{Re}_{\rm eff}^{0.687}\right), \frac{8}{3}\frac{Eo}{Eo + 4}\right]$$

and second correction to account for fluid-phase turbulence:

$$\mathsf{Re}_{\mathrm{eff}} = \frac{d_{\mathrm{p}}\rho_{\mathrm{f}}|\mathbf{U}_{\mathrm{f}} - \mathbf{U}_{\mathrm{p}}|}{\mu_{\mathrm{eff}}}, \quad \mu_{\mathrm{eff}} = \mu_{\mathrm{f}} + C_{2}\rho_{\mathrm{f}}\frac{k^{2}}{\varepsilon}$$

- C<sub>1</sub> and C<sub>2</sub> are fitting parameters
- For gas–liquid systems:  $C_2 = 0.01$  and  $C_1 = -1.8$ , predict well gas hold-up

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# Mesoscale Model for Momentum Transfer

### Additional forces

• Virtual mass and (Saffman) lift force:

$$\langle \mathbf{A}_{\rm fp} \rangle_1 = \frac{\rho_{\rm f} C_{\rm vm}}{\rho_{\rm p} \gamma} \left( \mathbf{U}_{\rm f} - \mathbf{U}_{\rm p} \right) \cdot \boldsymbol{\nabla} \mathbf{U}_{\rm f} + \frac{\rho_{\rm f} C_{\rm L}}{\rho_{\rm p} \gamma} \left( \mathbf{U}_{\rm f} - \mathbf{U}_{\rm p} \right) \times (\boldsymbol{\nabla} \times \mathbf{U}_{\rm f})$$

where  $\gamma$  effective volume coefficient,  $C_{\rm L} = 0.25$  and  $C_{\rm vm} = 0.5$ 

Boussinesq-Basset history force:

$$\langle \mathbf{A}_{\rm fp} \rangle_1 = \frac{9}{d_{\rm p}} \frac{\rho_{\rm f}}{\rho_{\rm p}} \sqrt{\frac{\nu_{\rm f}}{\pi}} \int_{-\infty}^t \frac{1}{\sqrt{t-\tau}} \left( \frac{\mathrm{D}\mathbf{U}_{\rm f}}{\mathrm{D}\tau} - \frac{\mathrm{d}\mathbf{U}_{\rm p}}{\mathrm{d}\tau} \right) \mathrm{d}\tau$$

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### Mesoscale Model for Momentum Transfer

### Additional forces

• Brownian force:

$$\langle \mathbf{A}_{\rm fp} \rangle_1 = \frac{1}{M_{\rm p}} \left( 12 d_{\rm p} \mu_{\rm f} k_{\rm B} T_{\rm f} \right)^{1/2} \mathbf{W}(t)$$

• Thermophoretic force for spherical particles and large Knudsen numbers (e.g., nanoparticles in flames):

$$\langle \mathbf{A}_{\rm fp} \rangle_1 = -\frac{6 p_{\rm f} \lambda_{\rm f}}{\pi T_{\rm f} \rho_{\rm p} d_{\rm p}} \frac{\partial T_{\rm f}}{\partial \mathbf{x}}$$

• Knudsen numbers smaller than one (temp. gradient within particle):

$$\langle \mathbf{A}_{\rm fp} \rangle_1 = -\left(\frac{36\nu_{\rm f}^2 C_{\rm s}}{T_{\rm f} d_{\rm p}^2}\right) \left(\frac{\rho_{\rm f}}{\rho_{\rm p}}\right) \left(\frac{1}{1+6C_{\rm m}{\rm Kn}}\right) \left(\frac{k_{\rm f}/k_{\rm p}+2C_{\rm t}{\rm Kn}}{1+2k_{\rm f}/k_{\rm p}+4C_{\rm t}{\rm Kn}}\right) \frac{\partial T_{\rm f}}{\partial \mathbf{x}}$$

 $k_{\rm f}$  and  $k_{\rm p}$  thermal conductivities of fluid and particle,  $C_{\rm s} = 1.17$  thermal slip coefficient,  $C_{\rm t} = 2.18$  thermal exchange coefficient,  $C_{\rm m} = 1.14$  momentum exchange coefficient

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# Mesoscale Model for Mass Transfer

### Mesoscale variables for particle size

- (Truely) Equidimensional particles: nearly same size or spread in multiple directions and have constant material density
- Single internal coordinate: particle mass (or volume), particle surface area or particle length (V<sub>p</sub> = k<sub>V</sub>d<sup>3</sup><sub>p</sub> and A<sub>p</sub> = k<sub>A</sub>d<sup>2</sup><sub>p</sub>)
- Extension to other systems: possible when particle shrinks or grows without changing its shape and morphology
- Define one characteristic length,  $d_p^*$ , express real particle volume and surface area:  $V_p = k_V^* (d_p^*)^3$  and  $A_p = k_A^* (d_p^*)^2$ , and introduce an equivalent length,  $d_p = \phi_c d_p^*$ , equal to:  $\phi_c = 6k_V^*/k_A^*$ , forcing equivalent or averaged shape factors to be:  $k_V = (k_A^*)^3/216(k_V^*)^2$  and  $k_A = (k_A^*)^3/36(k_V^*)^2$
- If particle size is (first) internal coordinate then:

$$\langle G_{\mathrm{p}1} \rangle_{\mathrm{l}} = \dot{\xi}_{\mathrm{p}1} = \dot{d}_{\mathrm{p}} = \frac{M_{\mathrm{w}}}{\rho_{\mathrm{p}}} \frac{k_{\mathrm{A}}}{3k_{\mathrm{V}}} J$$



### Mesoscale Model for Mass Transfer

### Mesoscale variables for particle size

- In case of non-equidimensional particles more than one internal coordinate must be used
- Example: needle-like particles described as rectangular parallelepiped with length *ξ*<sub>p1</sub> and equal width and depth *ξ*<sub>p2</sub>
- Particle volume:  $V_p = \xi_{p1}(\xi_{p2})^2$ ; particle surface area:  $A_p = 2(\xi_{p2})^2 + 4\xi_{p1}\xi_{p2}$
- If J<sub>12</sub>(U<sub>p</sub>, ξ<sub>p</sub>, U<sub>f</sub>, ξ<sub>f</sub>) molar flux on surface delimited by ξ<sub>p1</sub> and ξ<sub>p2</sub>, and J<sub>22</sub>(U<sub>p</sub>, ξ<sub>p</sub>, U<sub>f</sub>, ξ<sub>f</sub>) molar flux on surface delimited by ξ<sub>p2</sub> and ξ<sub>p2</sub>, resulting mesoscale models are:

$$\langle G_{p1} \rangle_1 = \dot{\xi}_{p1} = 2M_w J_{22} / \rho_p, \quad \langle G_{p2} \rangle_1 = \dot{\xi}_{p2} = 4M_w J_{12} / \rho_p$$

· Alternative description: particle volume and surface area

$$\dot{V}_{\rm p} = (\xi_{\rm p2})^2 \dot{\xi}_{\rm p1} + 2\xi_{\rm p1}\xi_{\rm p2}\dot{\xi}_{\rm p2}, \quad \dot{A}_{\rm p} = (2\xi_{\rm p2} + 4\xi_{\rm p1})\dot{\xi}_{\rm p2} + 4\xi_{\rm p2}\dot{\xi}_{\rm p1}$$

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### Mesoscale Model for Mass Transfer

- Particles described as fractal objects: size of the primary particle, *ξ*<sub>p1</sub> = *d*<sub>p</sub>, and number of primary particles, *ξ*<sub>p2</sub> = *N*<sub>p</sub>
  - Fractal dimension:  $R_{\rm g} = d_{\rm p}/2 \left(N_{\rm p}/k_{\rm g}\right)^{1/D_{\rm f}}$
  - Mass transfer does not change number of primary particles

$$\dot{\xi}_{p1} = \dot{d}_{p} = \frac{M_{w}}{\rho_{p}} \frac{k_{A}k_{c}}{3k_{V}}J$$
 and  $\dot{\xi}_{p2} = \dot{N}_{p} = 0$ 

Mass transfer causes obliteration

$$\dot{\xi}_{p1} = \dot{d}_{p} = \frac{M_{w}}{\rho_{p}} \frac{k_{A}k_{c}}{3k_{V}} \frac{1}{(3-D_{f})}J$$
 and  $\dot{\xi}_{p2} = \dot{N}_{p} = -\frac{M_{w}}{\rho_{p}} \frac{k_{A}k_{c}}{3k_{V}} \left(\frac{D_{f}}{3-D_{f}}\right) \frac{M_{p}}{d_{p}}J$ 

Mass transfer changes number of primary particles

$$\dot{\xi}_{p1} = \dot{d}_p = 0$$
 and  $\dot{\xi}_{p2} = \dot{N}_p = \frac{M_w}{\rho_p} \frac{N_p}{d_p} \frac{k_A k_c}{k_V} J$ 

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## Mesoscale Model for Mass Transfer

### Diffusion-controlled growth for equi-dimensional particles

Resulting growth rate

$$\dot{d}_{\rm p} = \frac{k_{\rm A}}{3k_{\rm V}} \frac{M_{\rm w}}{\rho_{\rm p}} k_{\rm d} c_{\rm eq} (S-1)$$

• Creeping (or Stokes) flow conditions and rigid sphere

$$Sh = 1 + (1 + Pe)^{1/3}$$

where  $Pe = Re_pSc$  (Sc =  $\nu/D$ , Sh =  $k_dd_p/D$ )

- For larger particle Reynolds numbers: Sh =  $2 + 0.724 Re_p^{0.48} Sc^{1/3}$ , valid for  $100 < Re_p \le 2000$  and Sh =  $2 + 0.425 Re_p^{0.55} Sc^{1/3}$ , valid for  $2000 < Re_p \le 10^5$
- For micron-sized (or smaller) particles moving in turbulent fluids: Sh =  $2.0 + 0.52 (\text{Re}_p^*)^{0.52} \text{Sc}^{1/3}$  where  $\text{Re}_p^* = \varepsilon_f^{1/3} d_p^{4/3} / v_f$  is modified particle Reynolds number



### Mesoscale Model for Mass Transfer

### Mass transfer to gas bubbles

- Rate of change of bubble mass:  $\dot{M}_{\rm p} = M_{\rm w} k_{\rm d} A_{\rm p} \Delta c$
- In case of gas bubbles their shape is not fixed, bubble aspect ratio: e.g.  $E = 1/(1 + 0.1613 \text{Eo}^{0.757})$
- · Real area of bubble:

$$\frac{A_{\rm p}}{A_{\rm eq}} = \frac{1}{2E^{2/3}} \left[ 1 + \frac{E^2}{2 \sqrt{1-E^2}} \ln \! \left( \frac{1 + \sqrt{1-E^2}}{1 - \sqrt{1-E^2}} \right) \right] \label{eq:Applied}$$

- Under creeping (or Stokes) flow conditions: Sh = 1 + (1 + 0.564Pe<sup>2/3</sup>)<sup>3/4</sup>, spherical particles with Re<sub>p</sub> ≥ 70 Sh =  $\frac{2}{\sqrt{\pi}} \left(1 - \frac{2.96}{\text{Re}_{p}^{1/2}}\right)^{1/2}$  Pe<sup>1/2</sup>; Reynolds number sufficiently large, term in parenthesis is small compared to unity: Sh = 2Pe<sup>1/2</sup> /  $\sqrt{\pi}$
- For turbulent systems:  $k_{\rm d} = cD^{0.5} (\varepsilon_{\rm f}/\nu_{\rm f})^{0.25}$

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### Mesoscale Model for Zero-Order Point Processes

 In zero-order point processes S<sub>1</sub> does not depend on NDF and usually represents rate of formation (i.e., nucleation or spinodal decomposition) of disperse phase:

$$S_1 = J(\boldsymbol{\phi}_{\rm f})\delta(\mathbf{v}_{\rm p} - \mathbf{U}_{\rm f})\delta(\boldsymbol{\xi}_{\rm p} - \boldsymbol{\xi}_{\rm pc})\delta(\mathbf{v}_{\rm f} - \mathbf{U}_{\rm f})\delta(\boldsymbol{\xi}_{\rm f} - \boldsymbol{\xi}_{\rm fc})$$

where  $J(\phi_{\rm f}) \ge 0$  is rate of formation of particles with properties  $\xi_{\rm pc}$ 

- Definitions consistent with mass balance: for example if ξ<sub>p1</sub> and ξ<sub>f1</sub> are masses, then ξ<sub>pc1</sub> = m<sub>c</sub> and ξ<sub>fc1</sub> = -m<sub>c</sub>
- Source terms for transport equations for total number concentration:

$$S_{\rm N} = \int S_1 \, \mathrm{d}\mathbf{v}_{\rm p} \, \mathrm{d}\boldsymbol{\xi}_{\rm p} \, \mathrm{d}\mathbf{v}_{\rm f} \, \mathrm{d}\boldsymbol{\xi}_{\rm f} = J$$

disperse-phase mass density:

$$S_{\rm M} = \int \xi_{\rm p1} S_1 \,\mathrm{d}\mathbf{v}_{\rm p} \,\mathrm{d}\boldsymbol{\xi}_{\rm p} \,\mathrm{d}\mathbf{v}_{\rm f} \,\mathrm{d}\boldsymbol{\xi}_{\rm f} = m_{\rm c} J$$

disperse-phase momentum density:

$$\varrho_{\mathbf{p}}[[\mathbf{S}]]_{\mathbf{p}} = \int \xi_{\mathbf{p}1} \mathbf{v}_{\mathbf{p}} S_1 \, \mathrm{d}\mathbf{v}_{\mathbf{p}} \, \mathrm{d}\xi_{\mathbf{p}} \, \mathrm{d}\mathbf{v}_{\mathbf{f}} \, \mathrm{d}\xi_{\mathbf{f}} = m_{\mathbf{c}} \mathbf{U}_{\mathbf{f}} J$$

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$$S_1 = J(\boldsymbol{\phi}_{\rm f})\delta(\mathbf{v}_{\rm p} - \mathbf{U}_{\rm f})\delta(\boldsymbol{\xi}_{\rm p} - \boldsymbol{\xi}_{\rm pc})\delta(\mathbf{v}_{\rm f} - \mathbf{U}_{\rm f})\delta(\boldsymbol{\xi}_{\rm f} - \boldsymbol{\xi}_{\rm fc})$$

where  $J(\phi_{\rm f}) \ge 0$  is rate of formation of particles with properties  $\xi_{\rm pc}$ 

- Definitions consistent with mass balance: for example if  $\xi_{p1}$  and  $\xi_{f1}$  are masses, then  $\xi_{pc1} = m_c$  and  $\xi_{fc1} = -m_c$
- Source terms for transport equations for total number concentration:

$$S_{\rm N} = \int S_1 \, \mathrm{d}\mathbf{v}_{\rm p} \, \mathrm{d}\boldsymbol{\xi}_{\rm p} \, \mathrm{d}\mathbf{v}_{\rm f} \, \mathrm{d}\boldsymbol{\xi}_{\rm f} = J$$

disperse-phase mass density:

$$S_{\rm M} = \int \xi_{\rm p1} S_1 \, \mathrm{d} \mathbf{v}_{\rm p} \, \mathrm{d} \boldsymbol{\xi}_{\rm p} \, \mathrm{d} \mathbf{v}_{\rm f} \, \mathrm{d} \boldsymbol{\xi}_{\rm f} = m_{\rm c} J$$

disperse-phase momentum density:

$$\varrho_{\mathbf{p}}[[\mathbf{S}]]_{\mathbf{p}} = \int \xi_{\mathbf{p}1} \mathbf{v}_{\mathbf{p}} S_1 \, \mathrm{d}\mathbf{v}_{\mathbf{p}} \, \mathrm{d}\xi_{\mathbf{p}} \, \mathrm{d}\mathbf{v}_{\mathbf{f}} \, \mathrm{d}\xi_{\mathbf{f}} = m_{\mathbf{c}} \mathbf{U}_{\mathbf{f}} J$$

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# Mesoscale Model for First-Order Point Processes

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- Source term in GPBE is usually written as:

 $\mathcal{S}_1 = h^+ - h^-$ 

where  $h^+$  is rate of production and  $h^-$  is rate of loss of particles due to first-order point processes

- First-order processes are generally quantified by b(v<sub>p</sub>, ξ<sub>p</sub>, v<sub>f</sub>, ξ<sub>f</sub>) dt, which is probability that a particle with velocity v<sub>p</sub> and internal coordinates ξ<sub>p</sub> in a fluid with velocity v<sub>f</sub> and internal coordinates ξ<sub>f</sub> undergoes process under investigation in infinitesimal time interval dt
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# Mesoscale Model for First-Order Point Processes

• In order to quantify rate of formation a conditional probability density (PDF) function that states probability of formation of daughter particle with  $\mathbf{v}_p$  and  $\boldsymbol{\xi}_p'$  from mother particle with  $\mathbf{v}_p$  and  $\boldsymbol{\xi}_p$  has to be formulated:  $P(\mathbf{v}_p', \boldsymbol{\xi}_p' | \mathbf{v}_p, \boldsymbol{\xi}_p)$ 

• PDF has to satisfy a normalization condition:

$$\int P(\mathbf{v}_{\rm p}',\boldsymbol{\xi}_{\rm p}'|\mathbf{v}_{\rm p},\boldsymbol{\xi}_{\rm p})\,\mathrm{d}\mathbf{v}_{\rm p}'\mathrm{d}\boldsymbol{\xi}_{\rm p}'=1$$

 Instead of PDF an equivalent formulation in terms of a corresponding conditional NDF, N(v'<sub>p</sub>, ξ'<sub>p</sub>|v<sub>p</sub>, ξ<sub>p</sub>), is used:

$$\int N(\mathbf{v}_{\mathrm{p}}',\boldsymbol{\xi}_{\mathrm{p}}'|\mathbf{v}_{\mathrm{p}},\boldsymbol{\xi}_{\mathrm{p}})\,\mathrm{d}\mathbf{v}_{\mathrm{p}}'\mathrm{d}\boldsymbol{\xi}_{\mathrm{p}}'=\nu(\mathbf{v}_{\mathrm{p}},\boldsymbol{\xi}_{\mathrm{p}})$$

where v is number of new particles formed by first-order process



## Mesoscale Model for First-Order Point Processes

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#### Mesoscale Model for First-Order Point Processes

 Rate of formation of new particles due to first-order discontinuous processes can be expressed as

$$h^{+}(\mathbf{v}_{p}, \boldsymbol{\xi}_{p}, \mathbf{v}_{f}, \boldsymbol{\xi}_{f}) = \int N(\mathbf{v}_{p}, \boldsymbol{\xi}_{p} | \mathbf{v}_{p}', \boldsymbol{\xi}_{p}') b(\mathbf{v}_{p}', \boldsymbol{\xi}_{p}', \mathbf{v}_{f}, \boldsymbol{\xi}_{f}) n(\mathbf{v}_{p}', \boldsymbol{\xi}_{p}', \mathbf{v}_{f}, \boldsymbol{\xi}_{f}) d\mathbf{v}_{p}' d\boldsymbol{\xi}_{p}'$$

• In terms of P

$$h^{+}(\mathbf{v}_{p}, \boldsymbol{\xi}_{p}, \mathbf{v}_{f}, \boldsymbol{\xi}_{f}) = \int v(\mathbf{v}_{p}', \boldsymbol{\xi}_{p}') P(\mathbf{v}_{p}, \boldsymbol{\xi}_{p} | \mathbf{v}_{p}', \boldsymbol{\xi}_{p}') b(\mathbf{v}_{p}', \boldsymbol{\xi}_{p}', \mathbf{v}_{f}, \boldsymbol{\xi}_{f}) n(\mathbf{v}_{p}', \boldsymbol{\xi}_{p}', \mathbf{v}_{f}, \boldsymbol{\xi}_{f}) d\mathbf{v}_{p}' d\boldsymbol{\xi}_{p}'$$

 Note that these expressions are written under assumption that fluid velocity and composition do not change during first-order process



#### Turbulent Breakage Kernel (or Frequency) for Fluid–Fluid Systems

Coulaloglou & Tavlarides (1977):

$$b = C_1 d_{\rm p}^{-2/3} \varepsilon_{\rm f}^{1/3} \exp\left(-\frac{C_2 \sigma}{\rho_{\rm p} \varepsilon_{\rm f}^{2/3} d_{\rm p}^{5/3}}\right)$$

• Alopaeus et al. (2002):

$$b = C_4 \varepsilon_{\rm f}^{1/3} {\rm erfc} \left( \sqrt{C_5 \frac{\sigma}{\rho_{\rm f} \varepsilon_{\rm f}^{2/3} d_{\rm p}^{5/3}} + C_6 \frac{\mu_{\rm f}}{\sqrt{\rho_{\rm f} \rho_{\rm p}} \varepsilon_{\rm f}^{1/3} d_{\rm p}^{4/3}}} \right)$$

#### • Luo & Svendsen (1996):

$$bN = 0.92 \left(\frac{\varepsilon_{\rm f}}{d_{\rm p}^{\prime 2}}\right)^{1/3} \int_{\zeta_{\rm min}}^{1} \frac{(1+\zeta)^2}{\zeta^{11/3}} \exp\left(-\frac{12c_{\rm f}\sigma}{\beta \rho_{\rm p} \varepsilon_{\rm f}^{2/3} d_{\rm p}^{\prime 5/3} \zeta^{11/3}}\right) \mathrm{d}\zeta$$

where  $\zeta = \eta_k/d'_p$ ,  $\beta = 3/2$ ,  $c_f = f^{2/3} + (1 - f)^{2/3} - 1$ ],  $f = (d_p/d'_p)^3$ ,  $d_p$  is size of daughter particle, and  $d'_p$  is size of parent particle

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#### Turbulent Breakage Kernel (or Frequency) for Fluid–Particle Systems

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- Particles larger than turbulent microscale: breakage caused by instantaneous normal stresses
- Particles smaller than turbulent microscale: breakage caused by shear stresses due to turbulent dynamic velocity differences:

$$b = \frac{1}{\sqrt{15}} \left(\frac{\varepsilon_{\rm f}}{\nu_{\rm f}}\right)^{1/2} \exp\left(-\frac{\tau_{\rm s}}{\mu_{\rm f}(\varepsilon_{\rm f}/\nu_{\rm f})^{1/2}}\right)$$

- Aggregate strength:  $\tau_s = 9k_{co}\phi_p F/(8\pi d_o)$  where  $d_o$  diameter of primary particle,  $k_{co}$  coordination number, F inter-particle force can be computed as  $F = A_H d_o/(12H_o^2)$
- Coordination number depends on aggregate structure:  $k_c \approx 15\phi_p^{1.2}$  where  $\phi_p$  is volume fraction of solid within aggregates  $\phi_p = (0.414D_f 0.211)(d_p/d_o)^{D_f-3}$



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#### **Daughter Distribution Function**

 Simplest functional form is summation of delta functions (ν: number of daughters; ξ'<sub>p</sub>: parent particle; ξ<sub>p</sub>: daughter particle; ξ<sub>i</sub>(ξ'<sub>p</sub>) function stating relationship between i<sup>th</sup> daughter and parent):

$$N(\boldsymbol{\xi}_{\mathrm{p}}|\boldsymbol{\xi}_{\mathrm{p}}') = \sum_{i=1}^{\nu} \delta\left[\boldsymbol{\xi}_{\mathrm{p}} - \boldsymbol{\xi}_{i}(\boldsymbol{\xi}_{\mathrm{p}}')\right]$$

- *ξ<sub>i</sub>*(*ξ'*<sub>p</sub>) is formulated by respecting additional constraints (conservation of mass!)
- Binary breakage (v = 2): two identical fragments → symmetric breakage; very unequal fragments: erosion
- Often diversity of particles induces many simultaneous phenomena and continuous distributions are used
- Uniform distribution (particle mass internal coordinate)

$$N(m|m') = \begin{cases} 0 & m < 0\\ \frac{v}{m'} & 0 \le m \le m'\\ 0 & m > m' \end{cases}$$



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$$N(m|m') = \begin{cases} 0 & m < 0\\ \frac{\nu}{m'} & 0 \le m \le m'\\ 0 & m > m' \end{cases}$$



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#### **Daughter Distribution Function**

Simplest functional form is summation of delta functions (ν: number of daughters; ξ'<sub>p</sub>: parent particle; ξ<sub>p</sub>: daughter particle; ξ<sub>i</sub>(ξ'<sub>p</sub>) function stating relationship between i<sup>th</sup> daughter and parent):

$$N(\boldsymbol{\xi}_{\mathrm{p}}|\boldsymbol{\xi}_{\mathrm{p}}') = \sum_{i=1}^{\nu} \delta\left[\boldsymbol{\xi}_{\mathrm{p}} - \boldsymbol{\xi}_{i}(\boldsymbol{\xi}_{\mathrm{p}}')\right]$$

- \$\xi\_i(\xi\_p')\$ is formulated by respecting additional constraints (conservation of mass!)
- Binary breakage (v = 2): two identical fragments → symmetric breakage; very unequal fragments: erosion
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#### **Daughter Distribution Function**

• By imposing that mass of formed fragments sum up to mass of parent particle

$$\int_0^{m'} mN(m|m') \,\mathrm{d}m = \frac{\nu m'}{2}$$

it is easy to show that such a function is consistent only for binary breakage (i.e., v = 2)

• Binary parabolic distribution ( $0 \le C \le 3$ )

$$N(m|m') = \begin{cases} 0 & m < 0\\ C + \left(1 - \frac{C}{2}\right) \left[24\left(\frac{m}{m'}\right)^2 - 24\left(\frac{m}{m'}\right) + 6\right] & 0 \le m \le m'\\ 0 & m > m' \end{cases}$$

- For 0 ≤ C < 2 formation of different-sized fragments (i.e., erosion) is likely, whereas for 2 < C ≤ 3 symmetric breakage is more probable</li>
- C = 2 recovers uniform distribution



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#### **Daughter Distribution Function**

- Distribution can also be written in terms of particle size  $d_p$ :  $N(d_p|d'_p) = N(m|m')\partial m/\partial d_p$  where  $\partial m/\partial d_p = 3\rho_p k_V d_p^2$
- Formation of three fragments (Coulaloglou & Tavlarides, 1977)

$$N(d_{\rm p}|d_{\rm p}') = \frac{135d_{\rm p}^2}{{d_{\rm p}'}^3 \sqrt{2\pi}} \exp\left(-\frac{25}{2} \left[3\left(\frac{d_{\rm p}}{d_{\rm p}'}\right)^3\right]^2\right)$$

 β-distribution (v number of fragments formed; q greater than one: formation of v equally-sized fragments; q smaller than one: formation of one large fragment with v - 1 satellite fragments)

$$N(d_{\mathbf{p}}|d_{\mathbf{p}}') = \frac{\Gamma(q\nu)}{\Gamma(q)\Gamma(q(\nu-1))} \left[1 - \left(\frac{d_{\mathbf{p}}}{d_{\mathbf{p}}'}\right)^3\right]^{q(\nu-1)-1} \left(\frac{d_{\mathbf{p}}}{d_{\mathbf{p}}'}\right)^{3q-1} \frac{3\nu}{d_{\mathbf{p}}'}$$



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#### **Daughter Distribution Function**

- In case of multiple internal coordinates (particle size,  $d_{\rm p},$  and composition,  $\phi)$ 

$$N(d_{\rm p},\phi|d_{\rm p}',\phi') = 180 \frac{d_{\rm p}^2}{d_{\rm p}'^3} \left(\frac{d_{\rm p}^3}{d_{\rm p}'^3}\right)^2 \left(1 - \frac{d_{\rm p}^3}{d_{\rm p}'^3}\right)^2 \delta\left(\phi - \frac{d_{\rm p}^3}{d_{\rm p}'^3}\phi'\right)$$

where  $d'_{\rm p}$  and  $\phi'$  represent properties of parent particle, while  $d_{\rm p}$  and  $\phi$  properties of daughter particles

- Fragmentation of fractal aggregates (particle volume,  $V_{\rm p}$ , and surface area,  $A_{\rm p}$ )

$$P(V_{\rm p}, A_{\rm p}|V_{\rm p}^{\prime}, A_{\rm p}^{\prime}) = 2\delta\left(V_{\rm p} - \frac{V_{\rm p}^{\prime}}{2}\right)\delta\left(A_{\rm p} - \frac{A_{\rm p}^{\prime}}{2}\right)$$



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- Second-order point processes involve two particles (i.e. coalescence, aggregation, collision) and their rate shows a quadratic dependence on NDF
  - Source term in GPBE:

$$\mathcal{S}_1 = h^+ - h^-$$

where  $h^+$  is rate of production and  $h^-$  is rate of loss of particles

- One particle is located in x' and is characterized by phase-space vector η'; second particle is located in x and has phase-space vector η̃
- Frequency of second-order point process: *a*(**x**', η'; **x**, **η**) (symmetric with respect to permutation of particles)
- Quantity *a*(**x**', η'; **x**, η̃) d*t* represents fraction of particles undergoing point process in time interval d*t*



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 n<sup>(2)</sup>(t, x', η', x, η) dx'dη'dxdη represents expected number of particle pairs with (x', η') and (x, η)

• Closure is often used:  $n^{(2)}(t, \mathbf{x}', \eta', \tilde{\mathbf{x}}, \tilde{\eta}) \approx n(t, \mathbf{x}', \eta')n(t, \tilde{\mathbf{x}}, \tilde{\eta})$ 

- Based on these definitions, calculate number of events per unit time involving particle pairs (x', η') and (x̃, η̃) as a(x', η'; x̃, η̃)n(t, x', η')n(t, x̃, η̃) dx' dη' dx̃dη̃
- Total number of events occurring per unit time and unit volume involving *test* particles located near (x̃, η̃):

$$N_{\mathsf{e}}(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) = \int a(\mathbf{x}',\boldsymbol{\eta}';\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}})n(t,\mathbf{x}',\boldsymbol{\eta}')n(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}})\,\mathrm{d}\mathbf{x}'\mathrm{d}\boldsymbol{\eta}'$$

where integrals are over all locations x' and phase-space variables  $\eta'$  of field particle

• In most practical cases a closure is invoked:  $n(t, \mathbf{x}', \eta')n(t, \tilde{\mathbf{x}}, \tilde{\eta}) \approx n(t, \tilde{\mathbf{x}}, \eta')n(t, \tilde{\mathbf{x}}, \tilde{\eta})$ 



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 Based on these definitions, calculate number of events per unit time involving particle pairs (x', η') and (x̃, η̃) as a(x', η'; x̃, η̃)n(t, x', η')n(t, x̃, η̃) dx' dη' dx̃dη̃

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• By using this simplified expression and by inverting order of integrals

$$N_{\mathsf{e}}(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) = \int \left(\int a(\mathbf{x}',\boldsymbol{\eta}';\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) \,\mathrm{d}\mathbf{x}'\right) n(t,\tilde{\mathbf{x}},\boldsymbol{\eta}') n(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) \,\mathrm{d}\boldsymbol{\eta}'$$

Integral appearing between parenthesis is called kernel

$$\beta(\tilde{\mathbf{x}};\boldsymbol{\eta}',\tilde{\boldsymbol{\eta}}) = \int a(\mathbf{x}',\boldsymbol{\eta}';\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) \,\mathrm{d}\mathbf{x}'$$

- Kernels have dimensions of spatial volume per unit time (volumetric flux of particles undergoing second-order point process)
- Integral is used to derive kernels for different physical processes
- Particle encounters are dominated by local transport phenomena at distances larger than particle size and interaction potentials at shorter distances
- Kernels are naturally split in two terms: one accounts for particle transport in region of interaction (collision kernel) and other accounts for short-range interactions (aggregation efficiency)



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# Mesoscale Model for Second-Order Point Processes

• By using this simplified expression and by inverting order of integrals

$$N_{\rm e}(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) = \int \left(\int a(\mathbf{x}',\boldsymbol{\eta}';\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}})\,\mathrm{d}\mathbf{x}'\right) n(t,\tilde{\mathbf{x}},\boldsymbol{\eta}')n(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}})\,\mathrm{d}\boldsymbol{\eta}'$$

Integral appearing between parenthesis is called kernel

$$\beta(\tilde{\mathbf{x}}; \boldsymbol{\eta}', \tilde{\boldsymbol{\eta}}) = \int a(\mathbf{x}', \boldsymbol{\eta}'; \tilde{\mathbf{x}}, \tilde{\boldsymbol{\eta}}) \, \mathrm{d}\mathbf{x}'$$

- Kernels have dimensions of spatial volume per unit time (volumetric flux of particles undergoing second-order point process)
- Integral is used to derive kernels for different physical processes
- Particle encounters are dominated by local transport phenomena at distances larger than particle size and interaction potentials at shorter distances
- Kernels are naturally split in two terms: one accounts for particle transport in region of interaction (collision kernel) and other accounts for short-range interactions (aggregation efficiency)



• By using this simplified expression and by inverting order of integrals

$$N_{\rm e}(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}}) = \int \left(\int a(\mathbf{x}',\boldsymbol{\eta}';\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}})\,\mathrm{d}\mathbf{x}'\right) n(t,\tilde{\mathbf{x}},\boldsymbol{\eta}')n(t,\tilde{\mathbf{x}},\tilde{\boldsymbol{\eta}})\,\mathrm{d}\boldsymbol{\eta}'$$

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Positive source term is

$$h^{+}(t,\mathbf{x},\boldsymbol{\eta}) = \frac{1}{\delta} \int \beta(\boldsymbol{\eta}',\tilde{\boldsymbol{\eta}}) n(t,\mathbf{x},\boldsymbol{\eta}') n(t,\mathbf{x},\tilde{\boldsymbol{\eta}}) J(\tilde{\boldsymbol{\eta}},\boldsymbol{\eta}) \, \mathrm{d}\boldsymbol{\eta}'$$

 δ is symmetry factor (two for identical particles) and J(η̃, η) is Jacobian of variable transformation (with η' held constant)

$$J(\tilde{\eta}, \eta) = \left| \frac{\partial \tilde{\eta}}{\partial \eta} \right| = \left| \frac{\partial \tilde{\eta}_1}{\partial \eta_1} & \cdots & \frac{\partial \tilde{\eta}_1}{\partial \eta_M} \\ \vdots & \ddots & \vdots \\ \frac{\partial \tilde{\eta}_M}{\partial \eta_1} & \cdots & \frac{\partial \tilde{\eta}_M}{\partial \eta_M} \end{array} \right|$$

- Relationship between  $\tilde{\eta}$ ,  $\eta'$  and  $\eta$  is derived by continuity statements
- Negative source term is

$$h^{-}(t, \mathbf{x}, \boldsymbol{\eta}) = \int \beta(\boldsymbol{\eta}', \boldsymbol{\eta}) n(t, \mathbf{x}, \boldsymbol{\eta}') n(t, \mathbf{x}, \boldsymbol{\eta}) \,\mathrm{d}\boldsymbol{\eta}$$

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# Mesoscale Model for Second-Order Point Processes

Positive source term is

$$h^{+}(t,\mathbf{x},\boldsymbol{\eta}) = \frac{1}{\delta} \int \beta(\boldsymbol{\eta}',\tilde{\boldsymbol{\eta}}) n(t,\mathbf{x},\boldsymbol{\eta}') n(t,\mathbf{x},\tilde{\boldsymbol{\eta}}) J(\tilde{\boldsymbol{\eta}},\boldsymbol{\eta}) \, \mathrm{d}\boldsymbol{\eta}'$$

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### Mesoscale Model for Second-Order Point Processes

Positive source term is

$$h^{+}(t,\mathbf{x},\boldsymbol{\eta}) = \frac{1}{\delta} \int \beta(\boldsymbol{\eta}',\boldsymbol{\tilde{\eta}}) n(t,\mathbf{x},\boldsymbol{\eta}') n(t,\mathbf{x},\boldsymbol{\tilde{\eta}}) J(\boldsymbol{\tilde{\eta}},\boldsymbol{\eta}) \, \mathrm{d}\boldsymbol{\eta}'$$

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# Mesoscale Model for Second-Order Point Processes

Aggregation of fine particles

Internal coordinate particle mass (ξ<sub>p</sub> = ξ'<sub>p</sub> + ξ̃<sub>p</sub>; Jacobian equal to unity)

$$S_{1}(\xi_{p}) = \frac{1}{2} \int_{0}^{\xi_{p}} \beta(\xi', \tilde{\xi}_{p}) n(\xi'_{p}) n(\tilde{\xi}_{p}) \, \mathrm{d}\xi'_{p} - \int_{0}^{\infty} \beta(\xi'_{p}, \xi_{p}) n(\xi'_{p}) n(\xi'_{p}) \, \mathrm{d}\xi'_{p}$$

or in terms of final mass  $\xi_{\rm p}$  and of field particle mass  $\xi_{\rm p}'$ 

$$S_{1}(\xi_{p}) = \frac{1}{2} \int_{0}^{\xi_{p}} \beta(\xi_{p}', \xi_{p} - \xi_{p}') n(\xi_{p}') n(\xi_{p} - \xi') \, \mathrm{d}\xi' - \int_{0}^{\infty} \beta(\xi_{p}', \xi_{p}) n(\xi_{p}') \, \mathrm{d}\xi'_{p}$$

• Particle size  $(\tilde{\xi}_p = [\xi_p^3 - (\xi'_p)^3]^{1/3}$ ; Jacobian equal to  $\xi_p^2 [\xi_p^3 - (\xi'_p)^3]^{-2/3}$ )

$$S_{1}(\xi_{p}) = \frac{\xi_{p}^{2}}{2} \int_{0}^{\xi_{p}} \left[\xi_{p}^{3} - (\xi_{p}')^{3}\right]^{-2/3} \beta(\xi_{p}', [\xi_{p}^{3} - (\xi_{p}')^{3}]^{1/3}) n(\xi_{p}') \\ \times n([\xi_{p}^{3} - (\xi_{p}')^{3}]^{1/3}) \, \mathrm{d}\xi_{p}' - \int_{0}^{\infty} \beta(\xi_{p}', \xi_{p}) n(\xi_{p}') \, \mathrm{d}\xi_{p}'$$

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#### Coalescence of droplets

- Coalescing droplets characterized by particle mass  $\xi_p$  and velocity  $\mathbf{v}_p;$  continuity statements

$$\xi_{\rm p} = \xi_{\rm p}' + \tilde{\xi}_{\rm p}, \quad \xi_{\rm p} \mathbf{v}_{\rm p} = \xi_{\rm p}' \mathbf{v}_{\rm p}' + \tilde{\xi}_{\rm p} \tilde{\mathbf{v}}_{\rm p}$$

or, equivalently, as

$$\tilde{\xi}_{p} = \xi_{p} - \xi'_{p}, \quad \tilde{\mathbf{v}}_{p} = (\xi_{p}\mathbf{v}_{p} - \xi'_{p}\mathbf{v}'_{p})/(\xi_{p} - \xi'_{p})$$

• Jacobian for this nonlinear transformation:  $J = \frac{\partial (\xi_p, \mathbf{v}_p)}{\partial (\xi_p, \mathbf{v}_p)} = \left(\frac{\xi_p}{\xi_p - \xi'_p}\right)^3$  and resulting source term is

$$\begin{split} \mathcal{S}_{1}(\xi_{\mathrm{p}},\mathbf{v}_{\mathrm{p}}) &= \frac{1}{2} \int \left( \int_{0}^{\xi_{\mathrm{p}}} \beta(\xi_{\mathrm{p}}',\mathbf{v}_{\mathrm{p}}',\tilde{\xi}_{\mathrm{p}},\tilde{\mathbf{v}}_{\mathrm{p}}) n(\xi_{\mathrm{p}}',\mathbf{v}_{\mathrm{p}}') n(\tilde{\xi}_{\mathrm{p}},\tilde{\mathbf{v}}_{\mathrm{p}}) \frac{\xi_{\mathrm{p}}^{3}}{(\xi_{\mathrm{p}}-\xi_{\mathrm{p}}')^{3}} \, \mathrm{d}\xi_{\mathrm{p}}' \right) \\ &\times \, \mathrm{d}\mathbf{v}_{\mathrm{p}}' - \int \beta(\xi_{\mathrm{p}}',\mathbf{v}_{\mathrm{p}}',\xi_{\mathrm{p}},\mathbf{v}_{\mathrm{p}}) n(\xi_{\mathrm{p}}',\mathbf{v}_{\mathrm{p}}') n(\xi_{\mathrm{p}},\mathbf{v}_{\mathrm{p}}) \, \mathrm{d}\xi_{\mathrm{p}}' \, \mathrm{d}\mathbf{v}_{\mathrm{p}}' \end{split}$$



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#### Aggregation kernels due to Brownian motions for fine particles (i.e., $St_n = 0$ )

• Continuum or Stokes-Einstein regime (Kn<sup>\*</sup> =  $2\lambda_f/d_p < 1$ )

$$\beta(d_{\rm p}, d_{\rm p}') = \frac{2k_{\rm B}T_{\rm f}}{3\mu_{\rm f}} \left(\frac{1}{d_{\rm p}} + \frac{1}{d_{\rm p}'}\right) \left(d_{\rm p} + d_{\rm p}'\right) = \frac{2k_{\rm B}T_{\rm f}}{3\mu_{\rm f}} \frac{\left(d_{\rm p} + d_{\rm p}'\right)^2}{d_{\rm p}d_{\rm p}'}$$

• Free-molecular or Epstein regime (Kn<sup>\*</sup> =  $2\lambda_f/d_p > 1$ )

$$\beta(d_{\rm p}, d_{\rm p}') = \left(\frac{3}{4\pi}\right)^{1/6} \left(\frac{6k_{\rm B}T_{\rm f}}{\rho_{\rm p}}\right)^{1/2} \left(d_{\rm p} + d_{\rm p}'\right)^2 \left(\frac{1}{d_{\rm p}^3} + \frac{1}{d_{\rm p}'^3}\right)^{1/2}$$

Fuchs interpolating kernel

$$\beta = 4\pi \left(\Gamma + \Gamma'\right) \left(d_{\rm p} + d_{\rm p}'\right) \left[\frac{d_{\rm p} + d_{\rm p}'}{d_{\rm p} + d_{\rm p}' + \sqrt{g^2 + {g'}^2}} + \frac{4(\Gamma + \Gamma')}{(d_{\rm p} + d_{\rm p}')\sqrt{c^2 + {c'}^2}}\right]^{-1}$$

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# Mesoscale Model for Second-Order Point Processes

#### Aggregation kernels due to shear / velocity gradients

· Presence of spatial gradients in fluid velocity can induce aggregation

$$\beta(d_{\rm p}, d_{\rm p}') = \frac{4}{3}G_{\rm f} \left(d_{\rm p} + d_{\rm p}'\right)^3$$

laminar flow:  $G_{\rm f} = \frac{1}{2} \left( s_{ij} s_{ij} - s_{kk}^2 \right)$ , 2<sup>nd</sup> inv. of rate-of-strain tensor

In case of turbulent flows (particles smaller than Kolmogorov length scale)

$$\beta(d_{\rm p},d_{\rm p}') = \left(\frac{8\pi}{15}\right)^{1/2} \left(\frac{\nu_{\rm f}}{\varepsilon_{\rm f}}\right)^{1/2} \left(d_{\rm p}+d_{\rm p}'\right)^3 \approx 1.29 \left(\frac{\nu_{\rm f}}{\varepsilon_{\rm f}}\right)^{1/2} \left(d_{\rm p}+d_{\rm p}'\right)^3$$

· Particles larger than Kolmogorov length scale

$$\beta(d_{\rm p}, d_{\rm p}') = \left(\frac{8\pi}{3}\right)^{1/2} \varepsilon_{\rm f}^{1/3} \left(d_{\rm p} + d_{\rm p}'\right)^{7/2}$$

• Corrections available for  $St_p \neq 0$  (Ammar & Reeks, 2009)



# Mesoscale Model for Second-Order Point Processes

Aggregation efficiency for particles

- Short range forces accounted for in terms of aggregation efficiency: balance between attractive (van der Waals) and repulsive forces
- Repulsive forces: due to presence of fluid (double-layer repulsion or drainage of fluid)
- · Aggregation efficiency as inverse of Fuch's stability ratio

$$W = \left(\frac{d_{\rm p} + d_{\rm p}'}{2}\right) \int_0^\infty \exp\left(\frac{V(h)}{k_{\rm B}T_{\rm f}}\right) \left[\left(\frac{d_{\rm p} + d_{\rm p}'}{2}\right) + h\right]^{-2} \,\mathrm{d}h$$

*h* inter-particle distance,  $V(h) = V_a(h) + V_r(h)$  inter-particle potential

• Simplified expressions (van der Waals + double-layer):

 $\alpha = \frac{d_{\rm p} + d'_{\rm p}}{2\kappa} \exp\left(-\frac{\phi_{\rm max}}{k_{\rm B}T_{\rm f}}\right)$ , where  $\kappa$  is Debye-Huckel parameter and  $\phi_{\rm max}$  is energy barrier for particle aggregation

• Simplified expressions (van der Waals + viscous):  $\alpha = k \text{FI}^{-0.18}$ , where k is pre-factor of order unity and  $\text{FI} = 6\pi\mu_f (d_p + d'_p)G_f/A_H$ 

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#### Mesoscale Model for Second-Order Point Processes

Coalescence kernels for droplets (continuous phase gas)

Coalescence kernel calculated with concept of collisional cylinder

$$\beta(d_{\rm p}, d_{\rm p}', \mathbf{v}_{\rm r}) = \frac{\pi}{4} \left( d_{\rm p} + d_{\rm p}' \right)^2 |\mathbf{v}_{\rm r}| \eta(|\mathbf{v}_{\rm r}|)$$

- Function  $\eta \leq 1$  is coalescence efficiency that depends on Weber number: We =  $\frac{\rho_p |\mathbf{v}_r| d_p}{p}$  (relative importance of fluid inertia compared to interfacial tension)
- If We is smaller than 10 coalescence is very likely and efficiency  $\eta$  is very close to one
- As We increases coalescence is possible only for impact factor close to 0.2 (impact angles of about 10–15°; under these conditions coalescence is unlikely to happen (i.e.,  $\eta \approx 0$ ) and droplets after colliding are said to undergo lateral or head-on bouncing and reflective or stretching separation

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#### Coalescence kernels for bubbles (continuous phase liquid)

Small bubbles coalescing due to turbulent velocity fluctuations in liquid

$$\beta(d_{\rm p},d_{\rm p}') = 0.88\epsilon_{\rm f}^{1/3}(d_{\rm p}+d_{\rm p}')^2(d_{\rm p}^{2/3}+d_{\rm p}'^{2/3})^{1/2}\eta(d_{\rm p},d_{\rm p}')$$

· Coalescence efficiency is

$$\eta(d_{\rm p}, d_{\rm p}') = \exp\left(-6 \times 10^9 \ \frac{\mu_{\rm f} \rho_{\rm f} \epsilon_{\rm f}}{\sigma^2} \left(\frac{d_{\rm p} d_{\rm p}'}{d_{\rm p} + d_{\rm p}'}\right)^4\right)$$

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#### • Mesoscale models are very problem dependent!

- Models can be classified as continuous and discontinuous processes
- Discontinuous processes further divided into zero-, first- and second-order depending on number of particles involved
- Real physical models tend to be highly nonlinear, so no chance of finding analytical solutions for PBE/GPBE!



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Mesoscale Models for Physical and Chemical Processes

Formulation

Zero-Order Point Processes

First-Order Point Processes

Second-Order Point Processes

Solution Methods for Homogeneous Systems Class Method Monte Carlo Method of Moments Quadrature-Based Moment Methods

- Mesoscale models are very problem dependent!
- Models can be classified as continuous and discontinuous processes
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Quadrature-Based Moment Methods • Our objective is to solve GPBE for  $n(t, \mathbf{x}, \mathbf{v}, \boldsymbol{\xi})$ 

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• After integrating out particle velocity, find PBE for  $n(t, \mathbf{x}, \boldsymbol{\xi})$ 

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- Since transport in space is handled by CFD code, let us focus on other terms
- PBE for spatially homogeneous system with phase-space diffusion

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial \xi} \cdot \dot{\xi}n = \frac{\partial^2}{\partial \xi \partial \xi} : \mathbf{D}n + S$$

where  $n(t, \xi)$  and  $\xi = (\xi_1, ..., \xi_M)$ 

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## Class Method (Univariate)

- Let  $\xi$  denote unique internal coordinate and  $n(t,\xi)$  NDF
- Univariate PBE is

$$\frac{\partial n}{\partial t} + \frac{\partial \xi n}{\partial \xi} = \frac{\partial^2 Dn}{\partial \xi^2} + S$$

• Expressing drift, diffusion and point processes as a unique source term

$$\frac{\partial n}{\partial t} = S \equiv -\frac{\partial \dot{\xi}n}{\partial \xi} + \frac{\partial^2 Dn}{\partial \xi^2} + S$$

- $S(t,\xi,n)$  is functional that maps NDF into function of time and internal coordinate
- Define finite interval  $I_i$  for internal coordinate bounded by  $\xi_i$  and  $\xi_{i+1}$

$$\frac{\mathrm{d}}{\mathrm{d}t} \int_{\xi_i}^{\xi_{i+1}} n \,\mathrm{d}\xi = \int_{\xi_i}^{\xi_{i+1}} S \,\mathrm{d}\xi$$



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## Class Method (Univariate)

• If we denote number of particles in  $I_i$  interval as

$$N_i := \int_{\xi_i}^{\xi_{i+1}} n \,\mathrm{d}\xi$$

we recognize that

$$\frac{\mathrm{d}N_i}{\mathrm{d}t} = \int_{\xi_i}^{\xi_{i+1}} S \,\mathrm{d}\xi$$

where  $i = 1, \ldots, M$ , corresponding to following partition  $P_M$ 

$$\xi_1 < \xi_2 < \xi_3 < \dots < \xi_{M-1} < \xi_M < \xi_{M+1}$$

- Values of  $\xi_1$  and  $\xi_M$  are chosen so that excluded dynamics is negligible
- Number of intervals is fixed in order to achieve desired accuracy
- Resulting set of M ordinary differential equations (ODE) is unclosed!
- Use of discrete methods depends on restoration of autonomy, which lies in our ability to express right-hand side entirely in terms of dependent variables N<sub>i</sub>



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$$\int_{\xi_i}^{\xi_{i+1}} k_i(\xi) \,\mathrm{d}\xi = 1$$

• In case of **zero-order polynomial**, (constant) approximation is employed within each class

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## Class Method (Univariate)

- Let us start by discussing implication related to choice of a particular discretization and restoration of autonomy for second-order point processes
- Two different approaches: fixed-pivot technique and cell-average technique

• If  $\xi$  represents an additive property then

$$S = \frac{1}{2} \int_0^{\xi} \beta(\xi - \xi', \xi') n(\xi - \xi') n(\xi') \, \mathrm{d}\xi' - n(\xi) \int_0^{\infty} \beta(\xi, \xi') n(\xi') \, \mathrm{d}\xi'$$

resulting in

$$\frac{\mathrm{d}N_i}{\mathrm{d}t} = \frac{1}{2} \int_{\xi_i}^{\xi_{i+1}} \int_0^{\xi} \beta(\xi - \xi', \xi') n(\xi - \xi') n(\xi') \,\mathrm{d}\xi' \,\mathrm{d}\xi \\ - \int_{\xi}^{\xi_{i+1}} n(\xi) \int_0^{\infty} \beta(\xi, \xi') n(\xi') \,\mathrm{d}\xi' \,\mathrm{d}\xi$$



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# Class Method (Univariate)

• Expressing second integral as summation of integrals

$$\begin{aligned} \frac{\mathrm{d}N_i}{\mathrm{d}t} &= \frac{1}{2} \sum_{j=1}^{i-1} \int_{\xi_i}^{\xi_{i+1}} \int_{\xi_j}^{\xi_{j+1}} \beta(\xi - \xi', \xi') n_{\xi}(\xi - \xi') n_{\xi}(\xi') \,\mathrm{d}\xi' \mathrm{d}\xi \\ &- \sum_{j=1}^M \int_{\xi_i}^{\xi_{i+1}} n_{\xi}(\xi) \int_{\xi_j}^{\xi_{j+1}} \beta(\xi, \xi') n_{\xi}(\xi') \,\mathrm{d}\xi' \,\mathrm{d}\xi \end{aligned}$$

• Restoration of autonomy by using concept of pivotal points or pivots

$$\int_{\xi_i}^{\xi_{i+1}} n(\xi) \int_{\xi_j}^{\xi_{j+1}} \beta(\xi,\xi') n(\xi') \,\mathrm{d}\xi' \,\mathrm{d}\xi = N_i N_j \beta(\zeta_i,\zeta_j)$$

where  $\zeta_i$  and  $\zeta_j$  are pivotal points resulting in

$$\frac{\mathrm{d}N_i}{\mathrm{d}t} = \frac{1}{2} \sum_{j=1}^{i-1} N_j \sum_{(\zeta_j + \zeta_k) \in I_i} \beta(\zeta_k, \zeta_j) N_k - N_i \sum_{j=1}^M \beta(\zeta_i, \zeta_j) N_j$$



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- Fraction of new particle is assigned to  $I_i$  interval  $(\gamma_i^{(i)})$  and another fraction to  $I_{i+1}$   $(\gamma_{i+1}^{(i)})$
- Preservation of total number of particles

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- Fraction of new particle is assigned to  $I_i$  interval  $(\gamma_i^{(i)})$  and another fraction to  $I_{i+1}$   $(\gamma_{i+1}^{(i)})$
- Preservation of total number of particles

$$1=\gamma_i^{(i)}+\gamma_{i+1}^{(i)}$$

Preservation of total mass

$$\zeta_j + \zeta_k = \gamma_i^{(i)} \zeta_i + \gamma_{i+1}^{(i)} \zeta_{i+1}$$



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# Class Method (Univariate)

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# Class Method (Univariate)

- Preservation of  $r^{\text{th}}$ -order moment results in following reassignment equation:  $(\zeta_j + \zeta_k)^r = \gamma_i^{(i)} (\zeta_i)^r + \gamma_{i+1}^{(i)} (\zeta_{i+1})^r$ ,
- Two degrees of freedom are available, values of γ<sub>i</sub><sup>(i)</sup> and γ<sub>i+1</sub><sup>(i)</sup> are chosen in order to preserve two different moments of distribution
- For preserving moment of order zero, *m*<sub>0</sub>, and moment of order one, *m*<sub>1</sub>

$$\gamma_i^{(i)} = \frac{\zeta_{i+1} - (\zeta_j + \zeta_k)}{\zeta_{i+1} - \zeta_i}, \quad \gamma_{i+1}^{(i)} = \frac{(\zeta_j + \zeta_k) - \zeta_i}{\zeta_{i+1} - \zeta_i}$$

- This approach appears internally consistent only for two chosen moments of the NDF!
- For breakage condition for internal consistency is

$$\int_{\xi_i}^{\xi_{i+1}} \xi^r b(\xi|\xi_j) \,\mathrm{d}\xi = \zeta_i^r \int_{\xi_i}^{\xi_{i+1}} b(\xi|\xi_j) \,\mathrm{d}\xi$$

with  $\zeta_i > \zeta_j$  and where  $b(\xi|\xi_j)$  is daughter distribution function

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• Final equations for fixed-pivot technique

$$\frac{\mathrm{d}N_i}{\mathrm{d}t} = \frac{1}{2} \sum_{j=1}^{i-1} \beta_{i-j,j} N_{i-j} N_j - N_i \sum_{j=1}^M \beta_{i,j} N_j + \sum_{j=i+1}^M a_j b_{i,j} N_j - a_i N_i$$

- Geometrical grid:  $\xi_i = \frac{3}{4}\zeta_i, \ \xi_{i+1} = \frac{3}{2}\zeta_i, \ \zeta_{i+1} = 2\zeta_i$ , for  $i \in 1, \dots, M-1$
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$$-N_i \sum_{j=1}^{i-1} 2^{j-i} \beta_{i,j} N_j - N_i \sum_{j=1}^{i-1} \beta_{i,j} N_j$$



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# Class Method (Univariate)

Fixed-pivot technique can, in general, be formulated for any grid while preserving two moments of distribution of orders  $r_1$  and  $r_2$ 

$$\begin{split} \frac{\mathrm{d}N_i}{\mathrm{d}t} &= \sum_{j=i}^M N_j a_j \pi_{i,j} - a_i N_i + \sum_{\zeta_{i-1} \leq (\zeta_j + \zeta_k) < \zeta_i}^{j \geq k} \left( 1 - \frac{1}{2} \delta_{jk} \right) \left[ \gamma_i^{(i-1)} (\zeta_j + \zeta_k) \beta_{j,k} N_j N_k \right] \\ &+ \sum_{\zeta_i \leq (\zeta_j + \zeta_k) < \zeta_{i+1}}^{j \geq k} \left( 1 - \frac{1}{2} \delta_{jk} \right) \left[ \gamma_i^{(i)} (\zeta_j + \zeta_k) \beta_{j,k} N_j N_k \right] - N_i \sum_{j=1}^M \beta_{i,j} N_j \end{split}$$

where

$$\gamma_{i}^{(i)} = \frac{(\zeta_{j} + \zeta_{k})^{r_{1}}(\zeta_{i+1})^{r_{2}} - (\zeta_{j} + \zeta_{k})^{r_{2}}(\zeta_{i+1})^{r_{1}}}{(\zeta_{i})^{r_{1}}(\zeta_{i+1})^{r_{2}} - (\zeta_{i})^{r_{2}}(\zeta_{i+1})^{r_{1}}}$$
$$\gamma_{i}^{(i+1)} = \frac{(\zeta_{j} + \zeta_{k})^{r_{2}}(\zeta_{i})^{r_{1}} - (\zeta_{j} + \zeta_{k})^{r_{1}}(\zeta_{i})^{r_{2}}}{(\zeta_{i})^{r_{1}}(\zeta_{i+1})^{r_{2}} - (\zeta_{i})^{r_{2}}(\zeta_{i+1})^{r_{1}}}$$

and

$$\pi_{i,j} = \int_{\zeta_{i-1}}^{\zeta_i} \gamma_i^{(i-1)} b(\xi|\xi_j) \,\mathrm{d}\xi + \int_{\zeta_i}^{\zeta_{i+1}} \gamma_i^{(i-1)} b(\xi|\xi_j) \,\mathrm{d}\xi$$

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# Class Method (Univariate)

## ADVANTAGES

- Very intuitive (easy to develop tricks to solve problems)
- Generally stable

## DISADVANTAGES

- Method is consistent with respect to only TWO MOMENTS of NDF: particle mass and number
- One has to define a priori lower and upper limits of discretization
- Impossible to study for example: gelation or shattering
- Many (too many) classes to be used (e.g. 20–100): problematic especially with CFD codes where CPU time scales linearly with number of additional transport equations
- Very inefficient (each class does not know what others are doing)

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## Class Method (Univariate)

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**Class Method** Monte Carlo

Method of Moments

Quadrature-Based Moment Methods



## Class Method (Univariate)

#### ADVANTAGES

- Very intuitive (easy to develop tricks to solve problems)
- Generally stable

#### DISADVANTAGES

- Method is consistent with respect to only TWO MOMENTS of NDF: particle mass and number
- One has to define a priori lower and upper limits of discretization
- Impossible to study for example: gelation or shattering
- Many (too many) classes to be used (e.g. 20–100): problematic especially with CFD codes where CPU time scales linearly with number of additional transport equations
- Very inefficient (each class does not know what others are doing)

Computational Models for Polydisperse Particulate and Multiphase Systems

Rodney O. Fox International Francqui Professor

Mesoscale Models for Physical and Chemical Processes

Formulation

Zero-Order Point Processes

First-Order Point Processes

Second-Order Point Processes

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- Quadrature-Base Moment Methods

- Monte Carlo methods or Direct Simulation Monte Carlo (DSMC) are based on *artificial realizations* of behavior of multiphase system under investigation
- In MC methods evolution of each particle is tracked; continuous events are represented deterministically whereas discontinuous events are represented by random events occurring with specific and prescribed probabilities
- Connection with deterministic approach used in class methods: underlying multi-particle joint PDF is not averaged but is directly solved
- Solution is obtained by adopting methods for stochastic differential equations, leading to numerous realizations, representing different *sample paths*, that must be averaged out to eliminate low probability events



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## Monte Carlo Methods

- Group of *N* particles is randomly created (representing the given NDF) in computational domain or box and its evolution is directly tracked: time-driven simulations versus event-driven simulations
- After aggregation event for example N 1 particles remain in domain, whereas after breakage event N + 1 particles have to be tracked
- As simulation proceeds total number of particles changes, whereas total volume (or total mass) of particles in computational domain remains constant
- For this reason these methods are called **constant-volume** Monte Carlo
- Problems if *N* becomes to small or too large: **constant-number Monte Carlo**
- Coupling with CFD is done via compartment models



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## Method of Moments

- Basic idea behind **Method of Moments** is to solve evolution equations for moments of NDF
- · Generic moment of NDF is defined as

$$m_{k_1,k_2,...,k_M} = m(\mathbf{k}) = \left\langle \xi_1^{k_1} \xi_2^{k_2} \dots \xi_M^{k_M} \right\rangle := \int_{\Omega_{\xi}} n(\xi) \xi_1^{k_1} \xi_2^{k_2} \dots \xi_M^{k_M} \, \mathrm{d}\xi$$

where three different notations  $(m_{k_1,k_2,...,k_M}, m(\mathbf{k}), \langle \xi_1^{k_1} \xi_2^{k_2} \dots \xi_M^{k_M} \rangle)$  will be used interchangeably

•  $\mathbf{k} = (k_1, k_2, \dots, k_M)$  is called **exponent vector** 

General evolution equation for k<sup>th</sup> moment

$$\frac{\mathrm{d}m_{\mathbf{k}}}{\mathrm{d}t} = \overline{S}_{\mathbf{k}} = \int \boldsymbol{\xi}^{\mathbf{k}} \left( -\frac{\partial}{\partial \boldsymbol{\xi}} \cdot \dot{\boldsymbol{\xi}}n + \frac{\partial^2}{\partial \boldsymbol{\xi} \partial \boldsymbol{\xi}} : \mathbf{D}n + \mathcal{S} \right) \mathrm{d}\boldsymbol{\xi}$$

• By solving equations for moments, internal coordinates are integrated out, at expense of a crucial loss of information that must be retrieved (by reconstructing NDF for example)

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- Important advantage is that moments correspond to quantities that have meaningful physical interpretations and are therefore directly measurable
- This is a crucial point, since in many applications the NDF is not directly measured, but is inferred from measurements of integral quantities
- Two main issues arise when using MOM: **number of moments** to be tracked and **closure problem**
- Closure problem is impossibility of writing source term as function of moments only
- Issues of number of moments to be tracked and closure adopted are typically addressed together



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# Method of Moments (Univariate)

#### **Univariate PBE**

• Evolution equation for moment of order k ( $m_k := \int \xi^k n \, d\xi$ )

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \overline{S}_k = \int \xi^k \left( -\frac{\partial \dot{\xi}n}{\partial \xi} + \frac{\partial^2 Dn}{\partial \xi^2} + S \right) \mathrm{d}\xi$$

- In case of univariate distributions moment of order zero *m*<sub>0</sub> is total particle number density
- If internal coordinate is particle size, then  $m_1$  is total particle length density (number-average mean particle size:  $d_{10} = m_1/m_0$ )
- Moment of order two *m*<sub>2</sub> is proportional to total particle surface area per unit volume
- Moment of order three m<sub>3</sub> is related to total particle volume per unit volume (Sauter mean diameter: d<sub>32</sub> = m<sub>3</sub>/m<sub>2</sub>)
- Mean particle size weighted on particle volume:  $d_{43} = m_4/m_3$

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- Mean particle size weighted on particle volume:  $d_{43} = m_4/m_3$

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# Method of Moments (Univariate)

#### Univariate PBE

• Evolution equation for moment of order k ( $m_k := \int \xi^k n \, d\xi$ )

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \overline{S}_k = \int \xi^k \left( -\frac{\partial \dot{\xi}n}{\partial \xi} + \frac{\partial^2 Dn}{\partial \xi^2} + \mathcal{S} \right) \mathrm{d}\xi$$

- In case of univariate distributions moment of order zero *m*<sub>0</sub> is total particle number density
- If internal coordinate is particle size, then  $m_1$  is total particle length density (number-average mean particle size:  $d_{10} = m_1/m_0$ )
- Moment of order two *m*<sub>2</sub> is proportional to total particle surface area per unit volume
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# Method of Moments (Univariate)

#### **Univariate PBE**

• Evolution equation for moment of order k ( $m_k := \int \xi^k n \, d\xi$ )

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \overline{S}_k = \int \xi^k \left( -\frac{\partial \dot{\xi}n}{\partial \xi} + \frac{\partial^2 Dn}{\partial \xi^2} + \mathcal{S} \right) \mathrm{d}\xi$$

- In case of univariate distributions moment of order zero m<sub>0</sub> is total particle number density
- If internal coordinate is particle size, then m<sub>1</sub> is total particle length density (number-average mean particle size: d<sub>10</sub> = m<sub>1</sub>/m<sub>0</sub>)
- Moment of order two m<sub>2</sub> is proportional to total particle surface area per unit volume
- Moment of order three m<sub>3</sub> is related to total particle volume per unit volume (Sauter mean diameter: d<sub>32</sub> = m<sub>3</sub>/m<sub>2</sub>)
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# Method of Moments (Univariate)

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# Method of Moments (Univariate)

#### **Univariate PBE**

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# Method of Moments (Univariate)

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# Method of Moments (Univariate)

#### Univariate PBE: closure problem for aggregation

• In case of aggregation (mass as internal coordinate  $\xi$ )

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \frac{1}{2} \iint_0^\infty \beta(\xi,\xi') \left(\xi + \xi'\right)^k n(\xi) n(\xi') \,\mathrm{d}\xi \,\mathrm{d}\xi' - \int_0^\infty \xi^k n(\xi) \int_0^\infty \beta(\xi,\xi') n(\xi') \,\mathrm{d}\xi' \,\mathrm{d}\xi, \quad k \in 0, \dots, N$$

- In general it is impossible to close this set of equations
- Constant aggregation kernel  $\beta(\xi, \xi') = \beta_0$

 $\frac{\mathrm{d}m_k}{\mathrm{d}t} = \frac{\beta_0}{2} \iint_0^\infty \left(\xi + \xi'\right)^k n(\xi) n(\xi') \,\mathrm{d}\xi \,\mathrm{d}\xi' - \beta_0 m_0 m_k$ 

• General solution (for const. aggregation kernel)

$$\frac{\mathrm{d}m_0}{\mathrm{d}t} = -\frac{1}{2}\beta_0 m_0^2, \quad \frac{\mathrm{d}m_1}{\mathrm{d}t} = 0, \quad \frac{\mathrm{d}m_k}{\mathrm{d}t} = \frac{1}{2}\beta_0 \sum_{i=1}^{k-1} \binom{k}{i} m_i m_{k-i}$$



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#### Univariate PBE: closure problem for aggregation

In case of aggregation (mass as internal coordinate ξ)

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \frac{1}{2} \iint_0^\infty \beta(\xi,\xi') \left(\xi + \xi'\right)^k n(\xi) n(\xi') \,\mathrm{d}\xi \,\mathrm{d}\xi' - \int_0^\infty \xi^k n(\xi) \int_0^\infty \beta(\xi,\xi') n(\xi') \,\mathrm{d}\xi' \,\mathrm{d}\xi, \quad k \in 0, \dots, N$$

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#### Univariate PBE: closure problem for aggregation

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#### Univariate PBE: closure problem for aggregation

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General solution (for const. aggregation kernel)

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# Method of Moments (Univariate)

#### Univariate PBE: closure problem for aggregation

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General solution (for const. aggregation kernel)

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Method of Moments (Univariate)

#### Univariate PBE: closure problem for breakage

• In case of pure breakage (particle mass as internal coordinate)

$$\frac{\partial n}{\partial t} = \int_{\xi}^{\infty} a(\xi') b(\xi'|\xi) n(\xi') \,\mathrm{d}\xi' - a(\xi) n(\xi)$$

• Evolution equation for moment of order *k* is

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \int_0^\infty \xi^k \int_0^\infty a(\xi') b(\xi'|\xi) n(\xi') \,\mathrm{d}\xi' \mathrm{d}\xi - \int_0^\infty \xi^k a(\xi) n(\xi) \,\mathrm{d}\xi$$

- Analytical solutions available for constant breakage kernel: a(ξ) = a<sub>0</sub> and symmetric fragmentation b(ξ'|ξ) = 2δ (ξ - ξ'/2)
- Evolution equation for m<sub>k</sub> is

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = a_0 2^{1-k} m_k - a_0 m_k$$



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# Method of Moments (Univariate)

#### Univariate PBE: closure problem for breakage

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# Method of Moments (Univariate)

#### Univariate PBE: closure problem for breakage

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#### Particle number density model

- If particle mass is internal coordinate and two moments of NDF are tracked: m<sub>0</sub> = N and m<sub>1</sub> = ρ<sub>p</sub>α<sub>p</sub> = ρ<sub>p</sub>
- Mean particle size can be calculated:  $d_p = \left(\frac{m_1}{\rho_p k_V m_0}\right)^{1/3}$ , where  $k_V$  is particle volume shape factor and  $\rho_p$  is particle density
- Following reconstruction is done for NDF:  $n(t,\xi) = m_0 \delta \left(\xi \frac{m_1}{m_0}\right)$
- Final equations to be solved for pure aggregation are

$$\frac{\mathrm{d}m_0}{\mathrm{d}t} = -\frac{1}{2}\beta(d_{\mathrm{p}}, d_{\mathrm{p}})m_0^2, \quad \frac{\mathrm{d}m_1}{\mathrm{d}t} = 0$$

• With spatial transport (easy implementation in CFD codes)

$$\frac{\partial N}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot N \mathbf{U}_{\mathrm{N}} = -\frac{1}{2}\beta(d_{\mathrm{p}}, d_{\mathrm{p}})N^{2}, \quad \frac{\partial \varrho_{\mathrm{p}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\mathrm{p}}\mathbf{U}_{\mathrm{M}} = 0$$



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$$\frac{\mathrm{d}m_0}{\mathrm{d}t} = -\frac{1}{2}\beta(d_{\mathrm{p}}, d_{\mathrm{p}})m_0^2, \quad \frac{\mathrm{d}m_1}{\mathrm{d}t} = 0$$

• With spatial transport (easy implementation in CFD codes)

$$\frac{\partial N}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot N \mathbf{U}_{\mathrm{N}} = -\frac{1}{2}\beta(d_{\mathrm{p}}, d_{\mathrm{p}})N^{2}, \quad \frac{\partial \varrho_{\mathrm{p}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \varrho_{\mathrm{p}} \mathbf{U}_{\mathrm{M}} = 0$$



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## Method of Moments (Univariate)

#### Particle number density model

- If particle mass is internal coordinate and two moments of NDF are tracked: m<sub>0</sub> = N and m<sub>1</sub> = ρ<sub>p</sub>α<sub>p</sub> = ρ<sub>p</sub>
- Mean particle size can be calculated:  $d_{\rm p} = \left(\frac{m_{\rm I}}{\rho_{\rm p}k_{\rm V}m_0}\right)^{1/3}$ , where  $k_{\rm V}$  is particle volume shape factor and  $\rho_{\rm p}$  is particle density
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### **Quadrature-Based Moment Methods**

• Our original (univariate) problem was

$$\frac{\partial n}{\partial t} = S = -\frac{\partial}{\partial \xi} \left( \dot{\xi} n \right) + h$$

Instead we solve transport equations for moments

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = \overline{S}_k$$

with k = 0, 1, 2, ..., 2N - 1 and with specific initial condition  $m_k(0) = \int_{\Omega_c} n(0, \xi) \xi^k d\xi$ 

• Integration of ODE requires the evaluation of source term through quadrature approximation (Wheeler algorithm)



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# Quadrature Method of Moments

• For example, in case of continuous rate of change of internal coordinate

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = k \int_0^\infty \dot{\xi}(\xi) \xi^{k-1} n(\xi) \,\mathrm{d}\xi$$

Closure problem is overcome as

$$\frac{\mathrm{d}m_k}{\mathrm{d}t} = k \sum_{\alpha=1}^N \dot{\xi}(\xi_\alpha) (\xi_\alpha)^{k-1} w_\alpha$$

- where weights  $w_{\alpha}$  and nodes  $\xi_{\alpha}$  are calculated from PD or Wheeler algorithm from moments
- This method is called Quadrature Method of Moments



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### Quadrature Method of Moments

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$$\begin{aligned} \frac{\mathrm{d}m_k}{\mathrm{d}t} &= \overline{S}_k = \overline{J}_k + k \sum_{\alpha=1}^N \xi_\alpha^{k-1} \dot{\xi}_\alpha w_\alpha + k(k-1) \sum_{\alpha=1}^N \xi_\alpha^{k-2} D_\alpha w_\alpha \\ &+ \frac{1}{2} \sum_{\alpha=1}^N \sum_{\gamma=1}^N \left[ (\xi_\alpha + \xi_\gamma)^k - \xi_\alpha^k - \xi_\gamma^k \right] \beta_{\alpha,\gamma} w_\alpha w_\gamma + \sum_{\alpha=1}^N a_\alpha \overline{b}_\alpha^k w_\alpha - \sum_{\alpha=1}^N \xi_\alpha^k a_\alpha w_\alpha \end{aligned}$$

where  $\dot{\xi}_{\alpha} = \dot{\xi}(\xi_{\alpha}), D_{\alpha} = D(\xi_{\alpha}), \beta_{\alpha,\gamma} = \beta(\xi_{\alpha},\xi_{\gamma})$  and  $a_{\alpha} = a(\xi_{\alpha})$  and moments of daughter distribution function are  $\bar{b}_{\alpha}^{k} = \int \xi^{k} b(\xi|\xi_{\alpha}) d\xi$ 

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# Direct Quadrature Method of Moments

• Fact that closure problem is overcome with quadrature approximation

$$\int_{\Omega_{\xi}} n(\xi) g(\xi) \,\mathrm{d}\xi \approx \sum_{\alpha=1}^{N} w_{\alpha} g(\xi_{\alpha})$$

is equivalent to assumption that NDF is

$$n(\xi) = \sum_{\alpha=1}^{N} w_{\alpha} \delta\left(\xi - \xi_{\alpha}\right)$$

 Instead of tracking evolution for moments, evolution of weights and nodes in quadrature approximation could be directly tracked: Direct quadrature method of moments



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### Direct Quadrature Method of Moments

• If weights and nodes are continuous functions we obtain

$$\sum_{\alpha=1}^{N} \delta(\xi - \xi_{\alpha}) \left( \frac{\mathrm{d}w_{\alpha}}{\mathrm{d}t} \right) - \sum_{\alpha=1}^{N} \delta'(\xi - \xi_{\alpha}) \left( w_{\alpha} \frac{\mathrm{d}\xi_{\alpha}}{\mathrm{d}t} \right) = S(\xi)$$

• If weighted nodes (or weighted abscissas)  $\varsigma_{\alpha} = w_{\alpha}\xi_{\alpha}$  are introduced

$$\sum_{\alpha=1}^{N} \delta(\xi - \xi_{\alpha}) \left( \frac{\mathrm{d}w_{\alpha}}{\mathrm{d}t} \right) - \sum_{\alpha=1}^{N} \delta'(\xi - \xi_{\alpha}) \left( -\xi_{\alpha} \frac{\mathrm{d}w_{\alpha}}{\mathrm{d}t} + \frac{\mathrm{d}\zeta_{\alpha}}{\mathrm{d}t} \right) = S(\xi)$$

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### Direct Quadrature Method of Moments

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### **Direct Quadrature Method of Moments**

• We now define  $a_{\alpha}$  and  $b_{\alpha}$  to be source terms

$$\frac{\mathrm{d}w_{\alpha}}{\mathrm{d}t} = a_{\alpha}, \quad \frac{\mathrm{d}\varsigma_{\alpha}}{\mathrm{d}t} = b_{\alpha}$$

• Using these definitions we write a simpler form

$$\sum_{\alpha=1}^{N} \left[ \delta(\xi - \xi_{\alpha}) + \delta'(\xi - \xi_{\alpha})\xi_{\alpha} \right] a_{\alpha} - \sum_{\alpha=1}^{N} \delta'(\xi - \xi_{\alpha})b_{\alpha} = S(\xi)$$

 This equation can now be used to determine the unknown functions a<sub>α</sub> and b<sub>α</sub> by applying the moment transformation



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# **Direct Quadrature Method of Moments**

- DQMOM can be applied for any independent set of moments (number of moments MUST be equal the number of unknown functions)
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• Moment transform yields

$$(1-k)\sum_{\alpha=1}^{N}\xi_{\alpha}^{k}a_{\alpha}+k\sum_{\alpha=1}^{N}\xi_{\alpha}^{k-1}b_{\alpha}=\overline{S}_{k}$$

with 
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Mesoscale Models for Physical and Chemical Processes

Formulation

Zero-Order Point Processes

First-Order Point Processes

Second-Order Point Processes

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## **Direct Quadrature Method of Moments**

- DQMOM can be applied for any independent set of moments (number of moments MUST be equal the number of unknown functions)
- Knowing that

$$\int_{-\infty}^{+\infty} \xi^k \delta(\xi - \xi_\alpha) \, \mathrm{d}\xi = (\xi_\alpha)^k$$
$$\int_{-\infty}^{+\infty} \xi^k \delta'(\xi - \xi_\alpha) \, \mathrm{d}\xi = -k(\xi_\alpha)^{k-1}$$

Moment transform yields

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$$(1-k)\sum_{\alpha=1}^{N}\xi_{\alpha}^{k}a_{\alpha}+k\sum_{\alpha=1}^{N}\xi_{\alpha}^{k-1}b_{\alpha}=\overline{S}_{k}$$

with 
$$k = k_1, k_2, ..., k_{2N}$$

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### Direct Quadrature Method of Moments

• Linear system can be written in matrix form:

 $\mathbf{A}\boldsymbol{\alpha} = \mathbf{d}$ 

where

$$\boldsymbol{\alpha} = \begin{bmatrix} a_1 & \cdots & a_N & b_1 & \cdots & b_N \end{bmatrix}^T = \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix}$$
$$\mathbf{d} = \begin{bmatrix} \overline{S}_{k_1} & \cdots & \overline{S}_{k_{2N-1}} \end{bmatrix}^T$$

· Components of matrix A are



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Components of matrix A are

$$a_{ij} = \begin{cases} (1 - k_i) \, \xi_j^{k_i} & \text{if } 1 \le j \le N \\ k_i \xi_j^{k_i - 1} & \text{if } N + 1 \le j \le 2N \end{cases}$$



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### Direct Quadrature Method of Moments

If (as in QMOM) first 2N integer moments are chosen (i.e., k = 0,..., 2N - 1), matrix of linear system is



• A does not depend on weights  $w_{\alpha}$  and if abscissas  $\xi_{\alpha}$  are unique, then A will be full rank



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  - $\begin{bmatrix} 1 & \cdots & 1 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 1 & \cdots & 1 \\ -\xi_1^2 & \cdots & -\xi_N^2 & 2\xi_1 & \cdots & 2\xi_N \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 2(1-N)\xi_1^{2N-1} & \cdots & 2(1-N)\xi_N^{2N-1} & (2N-1)\xi_1^{2N-2} & \cdots & (2N-1)\xi_N^{2N-2} \end{bmatrix}$
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- Method is called Direct quadrature method of moments
- Evolution equations for weights and nodes of quadrature approximation are solved:

$$\frac{\mathrm{d}w_{\alpha}}{\mathrm{d}t} = a_{\alpha}, \quad \frac{\mathrm{d}w_{\alpha}\xi_{\alpha}}{\mathrm{d}t} = b_{\alpha}$$

• Source terms are calculated by inverting linear system and by using following initial condition:

$$w_{\alpha}(0) = w_{\alpha}^{0}, \quad \varsigma_{\alpha}(0) = w_{\alpha}^{0}\xi_{\alpha}^{0} \quad \text{for } k = 1, \dots, N$$

in turn calculated from initial moments



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### **Quadrature-Based Moment Methods**

- QBMM are very accurate in tracking evolution of moments of NDF: 4–8 moments do same job of many (e.g. 100) classes (see for example work of Marchisio et al. (2003) and Vanni (2000))
  - PD algorithm is very stable (if the moments are realizable) and for particular cases Wheeler algorithm is successful when PD fails
  - Important differences in QBMM arise when treating spatially inhomogeneous systems (discussed next)
  - In general increasing number of nodes of quadrature approximation and of moments to be tracked increases accuracy, unless problem is localized in phase space (e.g. fines dissolution)



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### Part 4

Computational Models for Polydisperse Particulate and Multiphase Systems

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QBMM for Spatially Inhomogeneous Systems

Inhomogeneous PBE

Multivariate QBMM

Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

# QBMM FOR SPATIALLY INHOMOGENEOUS SYSTEMS

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### Spatially Inhomogeneous PBE

• Spatially inhomogeneous PBE operating on  $n(\xi)$  is:

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \langle \mathbf{U}_p | \xi \rangle n = \frac{\partial}{\partial \mathbf{x}} \cdot D(\xi) \frac{\partial n}{\partial \mathbf{x}} - \frac{\partial}{\partial \xi} \dot{\xi}(\xi) n + h$$

where  $\langle \mathbf{U}_p | \xi \rangle$  and  $D(\xi)$  are known functions of  $\xi$ 

• Application of moment transform,  $M_k = \int n(\xi)\xi^k d\xi$ , generates several closure problems:

$$\frac{\partial M_k}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{U}_k M_k = \frac{\partial}{\partial \mathbf{x}} \cdot D_k \frac{\partial M_k}{\partial \mathbf{x}} + \overline{S}_k$$

where  $\mathbf{U}_k = \frac{\int \langle \mathbf{U}_p | \xi \rangle n(\xi) \xi^k \, \mathrm{d}\xi}{M_k}$  (similarly  $D_k$ ) and  $\overline{h}_k = \int h(\xi) \xi^k \, \mathrm{d}\xi$ • Solution with QMOM is as usual ...

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

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 From {M<sub>0</sub>, M<sub>1</sub>,..., M<sub>2N-1</sub>} quadrature formula of order N is constructed resulting in following approximation

$$M_k(t, \mathbf{x}) := \int_{\Omega_{\xi}} n(t, \mathbf{x}, \xi) \xi^k \, \mathrm{d}\xi \approx \sum_{\alpha=1}^N w_\alpha(t, \mathbf{x}) \xi_\alpha(t, \mathbf{x})^k$$

• that can be used to overcome different closure problems, for example:

$$\mathbf{U}_{k}(t,\mathbf{x}) := \frac{\int_{\Omega_{\xi}} \langle \mathbf{U}_{p} | \xi \rangle n(t,\mathbf{x},\xi) \xi^{k} \, \mathrm{d}\xi}{M_{k}} \approx \frac{\sum_{\alpha=1}^{N} \langle \mathbf{U}_{p} | \xi_{\alpha} \rangle w_{\alpha} \xi_{\alpha}^{k}}{M_{k}}$$

• By using different velocities,  $\mathbf{U}_k(t, \mathbf{x})$ , for different moments, we are capable of describing mixing and segregation patterns

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• From {*M*<sub>0</sub>, *M*<sub>1</sub>,..., *M*<sub>2N-1</sub>} quadrature formula of order *N* is constructed resulting in following approximation

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 By using different velocities, U<sub>k</sub>(t, x), for different moments, we are capable of describing mixing and segregation patterns

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Realizable Schemes Particle Trajectory Crossing

### Spatial Discretization in QMOM (1-D)

Solve transport equation for generic moment  $m_k$  with discretization schemes that PRESERVE realizable moments (constant  $U_p$ ):

$$\frac{\partial m_k}{\partial t} + \mathrm{U_p} \frac{\partial m_k}{\partial x} = \overline{S}_k$$

After spatial discretization (finite-volume method):

$$\frac{\mathrm{d}m_k^{\mathbf{P}}}{\mathrm{d}t} = \overline{S}_k^{\mathbf{P}} - \frac{\mathrm{U}_{\mathrm{p}}}{\Delta x} \left( m_k^{\mathbf{e}} - m_k^{\mathbf{w}} \right)$$

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With first-order upwind  $m_k^{\mathbf{e}} = m_k^{\mathbf{P}}$  and  $m_k^{\mathbf{w}} = m_k^{\mathbf{W}}$ 



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### Spatial Discretization in QMOM (1-D)

Solve transport equation for generic moment  $m_k$  with discretization schemes that PRESERVE realizable moments (constant  $U_p$ ):

$$\frac{\partial m_k}{\partial t} + \underbrace{\mathbf{U}_{\mathbf{p}}}_{\partial x} \frac{\partial m_k}{\partial x} = \overline{S}_k - \underbrace{\mathbf{U}_{\mathbf{p}}}_{\partial x} \frac{\partial m_k}{\partial x}$$

After spatial discretization (finite-volume method):

$$\frac{\mathrm{d}m_k^{\mathbf{P}}}{\mathrm{d}t} = \overline{S}_k^{\mathbf{P}} - \frac{\mathrm{U}_{\mathrm{P}}}{\Delta x} \left( m_k^{\mathbf{e}} - m_k^{\mathbf{w}} \right)$$

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After spatial discretization (finite-volume method):

$$\frac{\mathrm{d}m_k^{\mathbf{P}}}{\mathrm{d}t} = \overline{S}_k^{\mathbf{P}} - \frac{\mathrm{U}_{\mathrm{p}}}{\Delta x} \left( m_k^{\mathbf{e}} - m_k^{\mathbf{w}} \right)$$

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$$\frac{\mathrm{d}m_{k}^{\mathbf{P}}}{\mathrm{d}t} = \overline{S}_{k}^{\mathbf{P}} - \frac{\mathrm{U}_{\mathrm{p}}}{\Delta x} \left( m_{k}^{\mathbf{e}} - m_{k}^{\mathbf{w}} \right)$$

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With first-order upwind  $m_k^{\mathbf{e}} = m_k^{\mathbf{P}}$  and  $m_k^{\mathbf{w}} = m_k^{\mathbf{W}}$ 

Spatial discretization schemes based on first-order upwind always result in REALIZABLE moments Higher-order schemes (CDS, second-order upwind, QUICK, MUSCL) always result in UNREALIZABLE moments



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- One solution would be to evaluate moments at faces m<sup>e</sup><sub>k</sub> and m<sup>w</sup><sub>k</sub> through quadrature approximation
  - We know value of cell-average moments  $m_k^{W}$ ,  $m_k^{P}$ ,  $m_k^{E}$



- From these moments we can evaluate corresponding weights  $w^{\rm P}_{\alpha}$  and abscissas  $\xi^{\rm P}_{\alpha}$
- If weights at center of face are interpolated with  $p^{\text{th}}$ -order spatial reconstruction and abscissas are interpolated  $1^{\text{st}}$ -order spatial resulting moments will be valid if time step is well chosen
- This allows to improve numerical accuracy preserving realizable moments!

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- Also for multivariate cases QMOM can be used
- With QMOM transport equations for moments  $m_{\mathbf{k}}$  are solved, closure problem is overcome with quadrature approximation, and *N* weights  $w_{\alpha}$  and *N* vector abscissas (or nodes) of length  $M, \xi_{\alpha} = (\xi_{1,\alpha}, \xi_{2,\alpha}, \dots, \xi_{M,\alpha})$  are calculated using inversion (multidimensional) algorithms
- With DQMOM transport equations for weights  $w_{\alpha}$  and for weighted vector abscissas (or nodes)  $\xi_{\alpha} = (\xi_{1,\alpha}, \xi_{2,\alpha}, \dots, \xi_{M,\alpha})$ are solved, closure problem is overcome with quadrature approximation, and source terms are calculated by solving linear system
- All issues related to spatially inhomogeneous systems are still valid, so QMOM is preferred to conserve moments during transport



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$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{U}_p(\boldsymbol{\xi}) n = \frac{\partial}{\partial \mathbf{x}} \cdot D(\boldsymbol{\xi}) \frac{\partial n}{\partial \mathbf{x}} - \frac{\partial}{\partial \boldsymbol{\xi}} \cdot \dot{\boldsymbol{\xi}} n + h$$

and define generic integer moment:

$$m_{\mathbf{k}} := \int_{\Omega_{\boldsymbol{\xi}}} \boldsymbol{\xi}_1^{k_1} \cdots \boldsymbol{\xi}_M^{k_M} \boldsymbol{n}(t, \boldsymbol{\xi}) \, \mathrm{d}\boldsymbol{\xi}$$

equivalent notations  $m_{k_1,...,k_M} = m_{\mathbf{k}} = m(k_1,...,k_M) = m(\mathbf{k})$ Solve resulting moment transport equations (QMOM):

$$\frac{\partial m_{\mathbf{k}}}{\partial t} + \frac{\partial}{\partial \mathbf{x}} \cdot \mathbf{U}_{\mathbf{k}} m_{\mathbf{k}} - \frac{\partial}{\partial \mathbf{x}} \cdot D_{\mathbf{k}} \frac{\partial m_{\mathbf{k}}}{\partial \mathbf{x}} = \overline{S}_{\mathbf{k}} = \int_{\Omega_{\xi}} \boldsymbol{\xi}^{\mathbf{k}} \left[ -\frac{\partial}{\partial \boldsymbol{\xi}} \cdot \dot{\boldsymbol{\xi}} n + h \right] \mathrm{d}\boldsymbol{\xi}$$



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# Multidimensional Inversion Algorithms

**Brute-force QMOM** uses N(M + 1) moments to determine quadrature approximation by solving non-linear system:

$$m_{k_{i1},k_{i2},...,k_{iM}} = m(\mathbf{k}_i) = \sum_{\alpha=1}^N w_\alpha \prod_{\beta=1}^M \xi_{\beta,\alpha}^{k_{i\beta}} \quad 1 \le i \le N(M+1)$$

obtained with N(M + 1) different values of exponent vector  $\mathbf{k}_i = (k_{i1}, k_{i2}, \dots, k_{iM})$ ; for M = 2 and N = 2

$$\mathbf{K} = \begin{bmatrix} \mathbf{k}_1 \\ \mathbf{k}_2 \\ \mathbf{k}_3 \\ \mathbf{k}_4 \\ \mathbf{k}_5 \\ \mathbf{k}_6 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \\ 2 & 0 \\ 1 & 1 \\ 0 & \gamma_4 = 2 \\ 0 & \gamma_5 = 2 \\ 0 & 2 \end{bmatrix} \leftarrow \gamma_6 = 2$$



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# Multidimensional Inversion Algorithms

Let us write problem in terms of weights and weighted abscissas (instead of abscissas). The final non-linear system of N(M + 1) equations can be solved by employing Newton-Raphson iterative scheme:

$$\mathbf{Z}_{n+1} = \mathbf{Z}_n - \mathbf{A}^{-1}(\mathbf{K}, \mathbf{X}_n) \mathbf{F}(\mathbf{Z}_n)$$

Matrix A is the Jacobian of non-linear system:

$$a_{ij} = \begin{cases} (1 - \gamma_i) \prod_{\alpha=1}^{M} \xi_{\alpha,p}^{k_{i\alpha}} & \text{for } p = j, \text{ if } 1 \leq j \leq N \\ \left(\frac{k_{i1}}{\xi_{1,p}}\right) \prod_{\alpha=1}^{M} \xi_{\alpha,p}^{k_{i\alpha}} & \text{for } p = j - N, \text{ if } N + 1 \leq j \leq 2N \\ \vdots & \vdots \\ \left(\frac{k_{iM}}{\xi_{M,p}}\right) \prod_{\alpha=1}^{M} \xi_{\alpha,M}^{k_{i\alpha}} & \text{for } p = j - MN, \text{ if } MN + 1 \leq j \leq (1 + M)N \end{cases}$$

and is identical to the matrix of previous linear system



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- To perform calculations with both multivariate QMOM<sup>1</sup> matrix A must be non-singular (full rank)
- For M = 1 (univariate) problems this requirement is satisfied if nodes are distinct
- For multivariate cases, having distinct abscissas does not guarantee that  ${\bf A}$  will be full rank
- It can be shown that for fixed N and M, certain distinct moments are linearly dependent when M ≥ 1 for all possible sets of abscissas
- It is therefore necessary to identify moment set for which A is always non-singular for all non-degenerate points in phase space for given values of *M* and *N*

<sup>1</sup> If Brute-Force inversion algorithm is used

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- It can be shown that for fixed N and M, certain distinct moments are linearly dependent when M ≥ 1 for all possible sets of abscissas
- It is therefore necessary to identify moment set for which A is always non-singular for all non-degenerate points in phase space for given values of *M* and *N*

<sup>1</sup> If Brute-Force inversion algorithm is used

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#### **OPTIMAL MOMENT SET**

- **()** Optimal moment set consists of N(M + 1) distinct moments
- Optimal moment set will result in full-rank square matrix A for all possible sets of N distinct, non-degenerate abscissas
- Optimal moment set includes all linearly independent moments of a particular order γ<sub>i</sub> before adding moments of higher order in order to result in perfectly symmetric treatment of internal coordinates



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## **Optimal Moment Set**

Moments used for bivariate quadrature approximation (M = 2) for N = 2

In this case  $m_{0,3}$  is chosen as the third-order moment to saturate degrees of freedom

Moments used for bivariate quadrature approximation (M = 2) for N = 3

m(2,0)	m(2,1)		
m(1,0)	m(1,1)	m(1,2)	
m(0,0)	m(0,1)	m(0,2)	m(0,3)

In this case  $m_{2,1}$ ,  $m_{1,2}$  and  $m_{0,3}$  are chosen among third-order moments to saturate the degrees of freedom



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Realizable Schemes Particle Trajectory Crossing Optimal moment set for bivariate quadrature approximation (M = 2) for N = 4

 $\begin{array}{ll} m(3,0) & m(3,1) \\ m(2,0) & m(2,1) \\ m(1,0) & m(1,1) & m(1,2) & m(1,3) \\ m(0,0) & m(0,1) & m(0,2) & m(0,3) \end{array}$ 

When  $N^{1/M}$  is an integer, there exists an optimal moment set that is also symmetric

Optimal moment for bivariate quadrature approximation (M = 2) for N = 9

m(5,0)	m(5,1)	m(5,2)			
m(4,0)	m(4,1)	m(4,2)			
m(3,0)	m(3,1)	m(3,2)			
m(2,0)	m(2,1)	m(2,2)	m(2,3)	m(2,4)	m(2,5)
m(1,0)	m(1,1)	m(1,2)	m(1,3)	m(1,4)	m(1,5)
m(0,0)	m(0,1)	m(0,2)	m(0,3)	m(0,4)	m(0,5)



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- Brute-force methods need an initial guess very (very (very)) close to final solution
- Alternative approach is Tensor-product QMOM
- First *M* univariate quadratures are calculated from 'pure' moments in different directions
- These *M* quadratures nodes are used to define final nodes by tensor product
- Weights are calculated subsequently by forcing quadrature to reproduce moment set (by solving linear system)
- Example for M = 2



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# Tensor-Product Inversion Algorithm

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#### 4-point quadrature approximation for bivariate distribution

Using PD (or Wheeler) algorithm:

$$(m_{0,0}, m_{1,0}, m_{2,0}, m_{3,0}) \to \left(w_1^1, w_2^1; \xi_{1,1}^*, \xi_{1,2}^*\right)$$
$$(m_{0,0}, m_{0,1}, m_{0,2}, m_{0,3}) \to \left(w_1^2, w_2^2; \xi_{2,1}^*, \xi_{2,2}^*\right)$$

Using tensor product, final 4-point quadrature approximation is centered on bivariate nodes:

$$\begin{aligned} \boldsymbol{\xi}_1 &= \left[ \boldsymbol{\xi}_{1,1}^*, \boldsymbol{\xi}_{2,1}^* \right] \\ \boldsymbol{\xi}_2 &= \left[ \boldsymbol{\xi}_{1,1}^*, \boldsymbol{\xi}_{2,2}^* \right] \\ \boldsymbol{\xi}_3 &= \left[ \boldsymbol{\xi}_{1,2}^*, \boldsymbol{\xi}_{2,1}^* \right] \\ \boldsymbol{\xi}_4 &= \left[ \boldsymbol{\xi}_{1,2}^*, \boldsymbol{\xi}_{2,2}^* \right] \end{aligned}$$

Four weights w1, w2, w3, w4 are calculated by forcing moment subset to be reproduced

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# **Tensor-Product Inversion Algorithm**





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# **Tensor-Product Inversion Algorithm**

Moment set used to build a bivariate quadrature approximation (M = 2) for  $N = N_1N_2 = 4$  with tensor-product method

 $\begin{array}{ll} m(3,0) \\ m(2,0) \\ m(1,0) & m(1,1) \\ m(0,0) & m(0,1) & m(0,2) & m(0,3) \end{array}$ 

- Moments accommodated by quadrature approximation are:  $N_1N_2 \cdots N_M + N_1 + N_2 + \cdots + N_M$ , less than maximum: (M + 1)N
- For example for *M* = 2 for *N* = 4 instead of 12 moments used and correctly represented are 8!
- Depending on shape of distribution negative weights are sometimes obtained (particularly for large *N*)



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# **Tensor-Product Inversion Algorithm**

8-point trivariate quadrature approximation  $(M = 3, N_1 = N_2 = N_3 = 2, N = N_1N_2N_3 = 8)$ 

> Optimal set (N(M + 1)): 32 moments Moments actually used: 14





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- Methods based on **conditional density functions**  $n(\xi_1, \xi_2) = n_1(\xi_1)f_{21}(\xi_2|\xi_1) = n_2(\xi_2)f_{12}(\xi_1|\xi_2)$
- Univariate quadrature  $(N_1)$  calculated from the first  $2N_1 1$ :

$$\begin{array}{c} m_{0,0,\dots,0,0} \\ \vdots \\ m_{2N_1-1,0,\dots,0,0} \end{array} \xrightarrow{\text{PD/Wheeler}} \begin{pmatrix} w_1 \\ \vdots \\ w_{N_1} \end{pmatrix} \begin{pmatrix} \xi_{1;1} \\ \vdots \\ \xi_{1;N_1} \end{pmatrix}$$

resulting for example in:  $n(\xi_1, \xi_2) = \sum_{\alpha_1=1}^{N_1} \delta(\xi_1 - \xi_{1;\alpha}) f_{21}(\xi_2 | \xi_1)$ Generic moment becomes:

$$d_{k_1,k_2} = \iint_{\alpha_1=1} n(\xi_1,\xi_2) \xi_1^{k_1} \xi_2^{k_2} d\xi_1 d\xi_2$$
$$= \sum_{\alpha_1=1}^{N_1} \xi_{1;\alpha}^{k_1} \int f_{21}(\xi_2|\xi_{1;\alpha}) \xi_2^{k_2} d\xi_2$$

• Conditional moment: 
$$\left< \xi_2^{k_2} \right>_{\alpha_1} := \int f(\xi_2 | \xi_{1;\alpha_1}) \xi_2^{k_2} d\xi_2$$

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$$m_{k_1,k_2} = \iint_{\alpha_1=1} n(\xi_1,\xi_2) \xi_1^{k_1} \xi_2^{k_2} d\xi_1 d\xi_2$$
$$= \sum_{\alpha_1=1}^{N_1} \xi_{1,\alpha}^{k_1} \int_{21} (\xi_2|\xi_{1,\alpha}) \xi_2^{k_2} d\xi_2$$

• Conditional moment: 
$$\langle \xi_2^{k_2} \rangle_{\alpha_1} := \int f(\xi_2 | \xi_{1;\alpha_1}) \xi_2^{k_2} d\xi_2$$



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Realizable Schemes Particle Trajectory Crossing For each of these  $N_1$  nodes,  $2N_2 - 1$  conditional moments are calculated, and univariate quadratures  $N_2$  are determined (in direction  $\xi_2$ ): Conditional QMOM or CQMOM





# Inversion Algorithms Based on Conditional Moments

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Realizable Schemes

Particle Trajectory Crossing Moments used to build a bivariate quadrature approximation (M = 2) for  $N_1 = N_2 = 3$  using CQMOM with  $\xi_2$  conditioned on  $\xi_1$  (top) and  $\xi_1$  conditioned on  $\xi_2$  (bottom)

m(5,0)					
m(4,0)					
m(3,0)					
m(2,0)	m(2,1)	m(2,2)	m(2,3)	m(2,4)	m(2,5)
m(1,0)	m(1,1)	m(1,2)	m(1,3)	m(1,4)	m(1,5)
m(0,0)	m(0,1)	m(0,2)	m(0,3)	m(0,4)	m(0,5)
m(5,0)	m(5,1)	m(5,2)			
m(4,0)	m(4,1)	m(4,2)			
m(3,0)	m(3,1)	m(3,2)			
m(2,0)	m(2,1)	m(2,2)			
m(1,0)	m(1,1)	m(1,2)			
m(0,0)	m(0,1)	m(0,2)	m(0,3)	m(0,4)	m(0,5)



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# Comparison of Different Algorithms

# EXAMPLE

Determine two quadrature approximations of orders 4 and 9 for bivariate Gaussian distribution:

$$f(\xi_1,\xi_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \times \exp\left(-\frac{1}{2(1-\rho^2)} \left[\frac{(\xi_1-\mu_1)^2}{\sigma_1^2} + \frac{2\rho(\xi_1-\mu_1)(\xi_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(\xi_2-\mu_2)^2}{\sigma_2^2}\right]\right)$$

with  $\mu_1 = 10$ ,  $\mu_2 = 20$ ,  $\sigma_1 = \sigma_2 = 2$  and different  $\rho$  values, by employing the Brute-Force **BF-QMOM**, Tensor-Product **TP-QMOM** and **CQMOM**.



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Realizable Schemes Particle Trajectory Crossing  $\rho = 0.5 N = 4$ ; **BF-QMOM** (diamond), **TP-QMOM** (circle) and **CQMOM** (square)





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Realizable Schemes Particle Trajectory Crossing Particles have real, finite velocities

- GPBE has real, finite velocities
- Moment system  $\mathbf{M} = [M_0, M_1, M_2, M_3, M_4]$  from GPBE

$$\frac{\partial \mathbf{M}}{\partial t} + \frac{\partial \mathbf{F}(\mathbf{M})}{\partial x} = 0$$

should be a hyberbolic equation (i.e. real eigenvalues)

• How do we check?: use Jacobian matrix of  $\mathbf{F} = [M_1, M_2, M_3, M_4, M_5]$ 

	0	1		0	0 ]
∂F ∂M	0	0	1	0	0
	0	0		1	0
	0	0		0	1
					$\frac{\partial M_5}{\partial M_4}$

Five eigenvalues must be real and distinct

• For HyQMOM, choose *M*<sub>5</sub> such that system is hyperbolic

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Realizable Schemes Particle Trajectory Crossing Particles have real, finite velocitiesGPBE has real, finite velocities

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	[ 0	1		0	0 ]
∂F ∂M	0	0	1	0	0
	0	0		1	0
	0	0		0	1
					$\left[\frac{\partial M_5}{\partial M_4}\right]$

Five eigenvalues must be real and distinct

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- Particles have real, finite velocities
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	ΓO	1	0	0	0 ]
Э <b>Г</b>	0	0	1	0	0
$\frac{\partial \mathbf{F}}{\partial \mathbf{F}} =$	0	0	0	1	0
ðМ	0	0	0	0	1
	$\frac{\partial M_5}{\partial M_0}$	$\frac{\partial M_5}{\partial M_1}$	$\frac{\partial M_5}{\partial M_2}$	$\frac{\partial M_5}{\partial M_3}$	$\frac{\partial M_5}{\partial M_4}$

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Crossing



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- GPBE has real, finite velocities
- Moment system  $\mathbf{M} = [M_0, M_1, M_2, M_3, M_4]$  from GPBE

$$\frac{\partial \mathbf{M}}{\partial t} + \frac{\partial \mathbf{F}(\mathbf{M})}{\partial x} = 0$$

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• How do we check?: use Jacobian matrix of  $\mathbf{F} = [M_1, M_2, M_3, M_4, M_5]$ 

	[0]	1	0	0	0 ]
917	0	0	1	0	0
$\frac{\partial \mathbf{r}}{\partial \mathbf{r}} =$	0	0	0	1	0
дМ	0	0	0	0	1
	$\frac{\partial M_5}{\partial M_0}$	$\frac{\partial M_5}{\partial M_1}$	$\frac{\partial M_5}{\partial M_2}$	$\frac{\partial M_5}{\partial M_3}$	$\frac{\partial M_5}{\partial M_4}$

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Realizable Schemes Particle Trajectory Crossing • Approximate velocity NDF by  $(N \ge 2)$ 

$$n(u) \approx M_0 \sum_{\alpha=1}^N p_\alpha \delta(u - \bar{u} - u_\alpha)$$

where  $\bar{u} = M_1/M_0$ , and  $p_{\alpha}$  and  $u_{\alpha}$  are found from central moments:

$$C_i = \frac{1}{M_0} \int_{-\infty}^{+\infty} (u - \bar{u})^i n(u) \, \mathrm{d}u$$

• Fix C<sub>2N-1</sub> such that moment system is hyperbolic

• Given  $\{1, 0, C_2, \dots, C_{2N-2}\}$  and constraint on  $C_{2N-1}$ , apply QMOM  $\{1, 0, C_2, \dots, C_{2N-1}\} \xrightarrow{\text{QMOM}} \{p_1, p_2, \dots, p_N\}, \{u_1, u_2, \dots, u_N\}$ 



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• Given  $\{1, 0, C_2 \dots, C_{2N-2}\}$  and constraint on  $C_{2N-1}$ , apply QMOM  $\{1, 0, C_2 \dots, C_{2N-1}\} \xrightarrow{\text{QMOM}} \{p_1, p_2, \dots, p_N\}, \{u_1, u_2, \dots, u_N\}$ 



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- Fix C<sub>2N-1</sub> such that moment system is hyperbolic
- Given  $\{1, 0, C_2, \dots, C_{2N-2}\}$  and constraint on  $C_{2N-1}$ , apply QMOM

$$\{1, 0, C_2 \dots, C_{2N-1}\} \stackrel{\mathsf{QMOM}}{\Longrightarrow} \{p_1, p_2, \dots, p_N\}, \{u_1, u_2, \dots, u_N\}$$



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Realizable Schemes Particle Trajectory Crossing • Moment closure for kinetic flux in 1-D:

$$\partial_t M_{2N-2} + \partial_x \overline{M}_{2N-1} = 0 \implies \overline{M}_{2N-1} = M_0 \sum_{\alpha=1}^N p_\alpha (\overline{u} + u_\alpha)^{2N-1}$$

For 
$$N = 3$$
:  $\bar{M}_5 = M_0 \left[ p_1 (\bar{u} + u_1)^5 + p_2 \bar{u}^5 + p_3 (\bar{u} + u_3)^5 \right]$ 

• Theorem: Moment system for  $\{M_0, M_1, M_2, M_3, M_4\}$  with kinetic flux  $\overline{M}_5$  is hyperbolic with 5 distinct eigenvalues

$$\lambda_0 = \bar{u}, \ \lambda_{1,2,3,4} = \bar{u} + \frac{\sqrt{C_2}}{2} \left( q \pm \sqrt{4\eta - 3q^2 \pm 4\sqrt{(\eta - q^2)(\eta - q^2 - 1)}} \right)$$

where  $q = C_3 / C_2^{3/2}$  and  $\eta = C_4 / C_2^2$ 



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### Hyperbolic QMOM: Kinetic-Based Flux

• Kinetic-based flux in 1-D for  $\mathbf{M} = \{M_0, M_1, M_2, M_3, M_4\}$ :

$$\partial_t \mathbf{M} + \partial_x \mathbf{F}(\mathbf{M}) = 0 \implies F_n = \sum_{\alpha=0}^4 w_\alpha \lambda_\alpha^{n+1}$$

where  $\mathbf{F} = \{F_0, F_1, F_2, F_3, F_4\}$ 

• 5 eigenvalues are known, weights found from

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ \lambda_0 & \lambda_1 & \lambda_2 & \lambda_3 & \lambda_4 \\ \lambda_0^2 & \lambda_1^2 & \lambda_2^2 & \lambda_3^2 & \lambda_4^2 \\ \lambda_0^3 & \lambda_1^3 & \lambda_2^3 & \lambda_3^3 & \lambda_4^3 \\ \lambda_0^4 & \lambda_1^4 & \lambda_2^4 & \lambda_3^4 & \lambda_4^4 \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix} = \begin{bmatrix} M_0 \\ M_1 \\ M_2 \\ M_3 \\ M_4 \end{bmatrix}$$

and find that  $w_0 = 0 \implies$  system has 4 velocities

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# Hyperbolic QMOM: Kinetic-Based Flux

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### Hyperbolic QMOM: Kinetic-Based Flux

Define normalized eigenvalues λ<sub>α</sub> = ū + √C<sub>2</sub> μ<sub>α</sub> and normalized weights:

$$\begin{bmatrix} \mu_1 & \mu_2 & \mu_3 & \mu_4 \\ \mu_1^2 & \mu_2^2 & \mu_3^2 & \mu_4^2 \\ \mu_1^3 & \mu_2^3 & \mu_3^3 & \mu_4^3 \\ \mu_1^4 & \mu_2^4 & \mu_3^4 & \mu_4^4 \end{bmatrix} \begin{bmatrix} w_1' \\ w_2' \\ w_3' \\ w_4' \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ q \\ \eta \end{bmatrix}$$

- $\implies$  positive weights depend on q and  $\eta$
- Up/Down-wind flux splitting:

$$F_n = M_0 \sum_{\alpha=1}^4 w'_{\alpha} \lambda_{\alpha}^n \min(0, \lambda_{\alpha}) + M_0 \sum_{\alpha=1}^4 w'_{\alpha} \lambda_{\alpha}^n \max(0, \lambda_{\alpha})$$

#### is used in finite-volume solver

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Hyperbolic QMOM: Kinetic-Based Flux

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### Conditional HyQMOM for 2-D Phase Space

• Approximate 2-D velocity NDF by  $(N \ge 2)$ 

10 moments

$$n(u,v) \approx M_{0,0} \sum_{\alpha=1}^{N} \sum_{\beta=1}^{N} p_{\alpha} p_{\alpha\beta} \delta(u-\bar{u}-u_{\alpha}) \delta(v-\bar{v}-\bar{v}_{\alpha}-v_{\alpha\beta})$$

where  $\bar{v} = M_{0,1}/M_{0,0}$  and abscissas  $v_{\alpha\beta}$  and  $\bar{v}_{\alpha}$  are found from central moments:

$$C_{i,j} = \frac{1}{M_{0,0}} \int_{\mathbb{R}^2}^{\infty} (u - \bar{u})^i (v - \bar{v})^j n(u, v) \, \mathrm{d}u \, \mathrm{d}v$$

12 moments

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• Example  $N^2 = 9$  nodes, CQMOM applied to symmetric moment sets:

 $M_{0,0}$  $M_{10}$  $M_{20} = M_{30}$  $M_{40}$  $M_{0,0}$  $M_{10}$   $M_{20}$   $M_{30}$  $M_{40}$  $M_{0,1}$  $M_{11}$  $M_{0,1}$  $M_{11}$  $M_{2,1}$  $M_{0.2}$  $M_{0,2} = M_{1,2}$  $M_{0.3}$  $M_{0.3}$  $M_{0.4}$  $M_{0.4}$ 



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# Conditional HyQMOM for 2-D Phase Space

• Approximate 2-D velocity NDF by  $(N \ge 2)$ 

10 moments

$$n(u,v) \approx M_{0,0} \sum_{\alpha=1}^{N} \sum_{\beta=1}^{N} p_{\alpha} p_{\alpha\beta} \delta(u-\bar{u}-u_{\alpha}) \delta(v-\bar{v}-\bar{v}_{\alpha}-v_{\alpha\beta})$$

where  $\bar{v} = M_{0,1}/M_{0,0}$  and abscissas  $v_{\alpha\beta}$  and  $\bar{v}_{\alpha}$  are found from central moments:

$$C_{i,j} = \frac{1}{M_{0,0}} \int_{\mathbb{R}^2} (u - \bar{u})^i (v - \bar{v})^j n(u, v) \, \mathrm{d}u \, \mathrm{d}v$$

12 moments

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### Conditional HyQMOM for 2-D Phase Space

• With 10 moments,  $\bar{v}_{\alpha} = a_0 + a_1 u_{\alpha}$  is found from

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- With 12 moments,  $\bar{v}_{\alpha} = a_0 + a_1 u_{\alpha} + a_2 u_{\alpha}^2$  and  $C_{2|u_{\alpha}} = b_0 + b_1 u_{\alpha}$



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# Conditional HyQMOM for 2-D Phase Space

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$$\partial_t M_{1,1} + \partial_x \overline{M}_{2,1} = 0 \implies \overline{M}_{2,1} = M_{0,0} \sum_{\alpha=1}^3 p_\alpha (\overline{u} + u_\alpha)^2 (\overline{v} + \overline{v}_\alpha)$$

• Theorem: 10 moment system with kinetic flux is hyperbolic with 10 distinct eigenvectors

• Extension to 3-D phase space follows same logic: Example  $N^3 = 27$  nodes uses either 16 or 23 moments



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# Hyperbolic QMOM: Kinetic-Based Flux 2/3-D

• Kinetic-based flux in 2-D for 10 moments  $\mathbf{M} = \{M_{0,0}, M_{1,0}, M_{0,1}, \dots, M_{4,0}, M_{0,4}\}:$ 

$$\partial_t \mathbf{M} + \partial_x \mathbf{F}_x(\mathbf{M}) = 0 \implies F_n = \sum_{\alpha=0}^4 \lambda_\alpha M_{n|\lambda_\alpha}$$

where the 10 flux components are  $\mathbf{F}_{x} = \{F_{0,0}, F_{1,0}, F_{0,1}, \dots, F_{4,0}, F_{0,4}\}$ 

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### Hyperbolic QMOM: Kinetic-Based Flux 2/3-D

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Realizable Schemes Particle Trajectory Crossing • Kinetic-based flux for y direction:

$$\partial_t \mathbf{M} + \partial_y \mathbf{F}_y(\mathbf{M}) = 0 \implies F_n = \sum_{\alpha=0}^4 \lambda_\alpha M_{n|\lambda_\alpha}$$

is done in same way, except 5 eigenvalues are found using moments {*M*<sub>0,0</sub>, *M*<sub>0,1</sub>, *M*<sub>0,2</sub>, *M*<sub>0,3</sub>, *M*<sub>0,4</sub>}
Up/Down-wind flux splitting:

$$F_n = \sum_{\alpha=1}^4 M_{n|\lambda_\alpha} \min(0, \lambda_\alpha) + \sum_{\alpha=1}^4 M_{n|\lambda_\alpha} \max(0, \lambda_\alpha)$$

is used in finite-volume solver

In 3-D, definitions are analogous

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### Hyperbolic QMOM: Kinetic-Based Flux 2/3-D

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## HIGH-ORDER, REALIZABLE, KINETIC-BASED, FINITE-VOLUME METHODS



Given a set of transported moments, solve

$$\frac{\partial M_{kl}}{\partial t} + \frac{\partial M_{k+1l}}{\partial x} = k \int v^{k-1} \xi^l An \, \mathrm{d}v \, \mathrm{d}\xi + l \int v^k \xi^{l-1} Gn \, \mathrm{d}v \, \mathrm{d}\xi + \int v^k \xi^l \mathbb{C} \, \mathrm{d}v \, \mathrm{d}\xi$$

where RHS is closed using QBMM:

$$\frac{\partial M_{kl}}{\partial t} + \frac{\partial M_{k+1l}}{\partial x} = \sum_{\alpha=1}^{N} n_{\alpha} \left\{ k v_{\alpha}^{k-1} \xi_{\alpha}^{l} A_{\alpha} + l v_{\alpha}^{k} \xi_{\alpha}^{l-1} G_{\alpha} + v_{\alpha}^{k} \xi_{\alpha}^{l} \mathbb{C}_{\alpha} \right\}$$

Things to consider:

- How do we discretize the spatial fluxes?
- How do we update the moments in time?
- How can we ensure that the moments are always realizable?

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#### Kinetic-Based Spatial Fluxes in 1-D

Spatial fluxes can use kinetic formulation: e.g.  $\partial_t M_0 + \partial_x M_1 = 0$ 

$$M_{1} = Q_{1}^{-} + Q_{1}^{+}$$
  
=  $\int_{-\infty}^{0} u n^{*}(u) du + \int_{0}^{\infty} u n^{*}(u) du$ 

Using reconstructed  $n^*$ , downwind and upwind flux components are

$$Q_{1}^{-} = \sum_{\alpha=1}^{N} n_{\alpha} u_{\alpha} I_{(-\infty,0)}(u_{\alpha}) \qquad Q_{1}^{+} = \sum_{\alpha=1}^{N} n_{\alpha} u_{\alpha} I_{(0,\infty)}(u_{\alpha})$$

where  $I_{\mathbb{S}}(x)$  is the indicator function for the interval  $\mathbb{S}$ 

Kinetic-based fluxes are weakly hyperbolic with QMOM Using hyperbolic QMOM, they are hyperbolic



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## Kinetic-Based Spatial Fluxes in 1-D

Spatial fluxes can use kinetic formulation: e.g.  $\partial_t M_0 + \partial_x M_1 = 0$ 

$$M_1 = Q_1^- + Q_1^+$$
  
=  $\int_{-\infty}^0 u \, n^*(u) \, \mathrm{d}u + \int_0^\infty u \, n^*(u) \, \mathrm{d}u$ 

Using reconstructed  $n^*$ , downwind and upwind flux components are

$$Q_{1}^{-} = \sum_{\alpha=1}^{N} n_{\alpha} u_{\alpha} I_{(-\infty,0)}(u_{\alpha}) \qquad Q_{1}^{+} = \sum_{\alpha=1}^{N} n_{\alpha} u_{\alpha} I_{(0,\infty)}(u_{\alpha})$$

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#### Finite-Volume Method: Definitions I

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#### • 1-D advection problem:

$$\frac{\partial \mathbf{M}}{\partial t} + \frac{\partial \mathbf{F}(\mathbf{M})}{\partial x} = 0$$

where  $\mathbf{M} = \int \mathbf{K}(v)n(v) \, dv$  and  $\mathbf{F}(\mathbf{M}) = \int v \mathbf{K}(v)n(v) \, dv$ 

Finite-volume representation of moment vector:

$$\mathbf{M}_{i}^{n} \equiv \frac{1}{\Delta x} \int_{x_{i}}^{x_{i+1}} \mathbf{M}(t_{n}, x) \, \mathrm{d}x$$

• Finite-volume formula:  $\lambda = \Delta t / \Delta x$ 

$$\mathbf{M}_{i}^{n+1} = \mathbf{M}_{i}^{n} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{n}, \mathbf{M}_{i+\frac{1}{2},r}^{n} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{n}, \mathbf{M}_{i-\frac{1}{2},r}^{n} \right) \right]$$

where  $\mathbf{G}(\mathbf{M}_l, \mathbf{M}_r) = \int v^+ \mathbf{K}(v) n_l(v) \, \mathrm{d}v + \int v^- \mathbf{K}(v) n_r(v) \, \mathrm{d}v$ 

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#### Finite-Volume Method: Definitions II

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Realizable Schemes Particle Trajectory Crossing Reconstruction of  $n(t_n, x, v)$  in each cell:



Blue: 1<sup>st</sup> order reconstruction

Green: 2<sup>nd</sup> order reconstruction

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Particle Trajectory Crossing

- Flux functions: given  $\mathbf{M}_{i}^{n}$  define  $\mathbf{G}(\mathbf{M}_{l}, \mathbf{M}_{r})$  to achieve high-order spatial accuracy but keep  $\mathbf{M}_{i}^{n+1}$  realizable!
  - Discrete distribution function: Define

$$\mathbf{M}_i^{n+1} \equiv \int \mathbf{K}(v) \boldsymbol{h}_i(v) \, \mathrm{d}v$$

and finite-volume formula can be written as

 $h_i(v) = \lambda |v^-| n_{i+\frac{1}{2},r}^n + \lambda v^+ n_{i-\frac{1}{2},l}^n + n_i^n - \lambda |v^-| n_{i-\frac{1}{2},r}^n - \lambda v^+ n_{i+\frac{1}{2},l}^n$ 

black part  $\geq 0$ , red part can be negative)

Sufficient condition for realizable moments: *h<sub>i</sub>*(*v*) ≥ 0 for all *v* and *i*



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Particle Trajectory Crossing

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Sufficient condition for realizable moments: *h<sub>i</sub>*(*v*) ≥ 0 for all *v* and *i*



#### Realizable, High-Order, Spatial Fluxes

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Particle Trajectory Crossing

- First order:  $n_{i-\frac{1}{2},r}^n = n_{i+\frac{1}{2},l}^n = n_i^n$  so that  $h = \lambda |v^-| n_{i+1}^n + \lambda v^+ n_{i-1}^n + (1 - \lambda |v^-| - \lambda v^+) n_i^n \implies \frac{1}{|v^-| + v^+} \ge \lambda$ Moments are realizable, but scheme is diffusive ...
- Quasi-higher order: Let  $n_i^n = \sum_{\alpha} \rho_{\alpha,i}^n \delta(v v_{\alpha,i}^n)$ and define

$$\begin{split} n_{i-\frac{1}{2},r}^{n} &= \sum_{\alpha} \rho_{\alpha,i-\frac{1}{2},r}^{n} \delta(v-v_{\alpha,i}^{n}) \\ n_{i+\frac{1}{2},l}^{n} &= \sum_{\alpha} \rho_{\alpha,i+\frac{1}{2},l}^{n} \delta(v-v_{\alpha,i}^{n}) \end{split}$$

so that  $h = \lambda |v^{-}|n_{i+\frac{1}{2},r}^{n} + \lambda v^{+} n_{i-\frac{1}{2},l}^{n} + \sum_{\alpha} \left( \rho_{\alpha,l}^{n} - \lambda |v^{-}| \rho_{\alpha,l-\frac{1}{2},r}^{n} - \lambda v^{+} \rho_{\alpha,l+\frac{1}{2},l}^{n} \right) \delta(v - v_{\alpha,l}^{n})$   $\implies \min_{\alpha} \left( \frac{\rho_{\alpha,l}^{n}}{|v_{\alpha,l}^{-}| \rho_{\alpha,l+\frac{1}{2},l}^{n} - v_{\alpha,l+\frac{1}{2},l}^{n}} \right) \geq \lambda$ 

# Use high-order, finite-volume schemes only for the weights



#### Realizable, High-Order, Spatial Fluxes

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so that

$$h = \lambda |v^{-}|n_{i+\frac{1}{2},r}^{n} + \lambda v^{+}n_{i-\frac{1}{2},l}^{n} + \sum_{\alpha} \left( \rho_{\alpha,i}^{n} - \lambda |v^{-}|\rho_{\alpha,i-\frac{1}{2},r}^{n} - \lambda v^{+}\rho_{\alpha,i+\frac{1}{2},l}^{n} \right) \delta(v - v_{\alpha,i}^{n})$$

$$\implies \min_{\alpha} \left( \frac{\rho_{\alpha,i}^{n}}{|v_{\alpha,i}^{-}|\rho_{\alpha,i-\frac{1}{2},r}^{n} + v_{\alpha,i+\frac{1}{2},l}^{n}} \right) \ge \lambda$$

# Use high-order, finite-volume schemes only for the weights



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Particle Trajectory Crossing

#### • First-order explicit Euler:

$$\mathbf{M}_{i}^{n+1} = \mathbf{M}_{i}^{n} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{n}, \mathbf{M}_{i+\frac{1}{2},r}^{n} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{n}, \mathbf{M}_{i-\frac{1}{2},r}^{n} \right) \right]$$

is realizable because RHS is convex sum of  $\mathbf{M}_{i}^{n}$ 

• Second-order Runga-Kutta (RK2):

$$\mathbf{M}_{i}^{*} = \mathbf{M}_{i}^{n} - \frac{1}{2}\lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{n}, \mathbf{M}_{i+\frac{1}{2},r}^{n} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{n}, \mathbf{M}_{i-\frac{1}{2},r}^{n} \right) \right]$$
$$\mathbf{M}_{i}^{n+1} = \mathbf{M}_{i}^{n} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{*}, \mathbf{M}_{i+\frac{1}{2},r}^{*} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{*}, \mathbf{M}_{i-\frac{1}{2},r}^{*} \right) \right]$$

is not realizable because Step 2 is not convex sum



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#### • RK2SSP:

$$\begin{split} \mathbf{M}_{i}^{*} &= \mathbf{M}_{i}^{n} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{n}, \mathbf{M}_{i+\frac{1}{2},r}^{n} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{n}, \mathbf{M}_{i-\frac{1}{2},r}^{n} \right) \right] \\ \mathbf{M}_{i}^{**} &= \mathbf{M}_{i}^{*} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{*}, \mathbf{M}_{i+\frac{1}{2},r}^{*} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{n}, \mathbf{M}_{i-\frac{1}{2},r}^{*} \right) \right] \\ \mathbf{M}_{i}^{n+1} &= \frac{1}{2} \left( \mathbf{M}_{i}^{n} + \mathbf{M}_{i}^{**} \right) \end{split}$$

is realizable because RHS are all convex sums of realizable moments

 In general, explicit, high-order, strong stability-preserving schemes are realizable

# Achieve high-order in space and time on unstructured grids!



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Realizable Schemes

Particle Trajectory Crossing

# • **RK2SSP:** $\mathbf{M}_{i}^{*} = \mathbf{M}_{i}^{n} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{n}, \mathbf{M}_{i+\frac{1}{2},r}^{n} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{n}, \mathbf{M}_{i-\frac{1}{2},r}^{n} \right) \right]$ $\mathbf{M}_{i}^{**} = \mathbf{M}_{i}^{*} - \lambda \left[ \mathbf{G} \left( \mathbf{M}_{i+\frac{1}{2},l}^{*}, \mathbf{M}_{i+\frac{1}{2},r}^{*} \right) - \mathbf{G} \left( \mathbf{M}_{i-\frac{1}{2},l}^{*}, \mathbf{M}_{i-\frac{1}{2},r}^{*} \right) \right]$ $\mathbf{M}_{i}^{n+1} = \frac{1}{2} \left( \mathbf{M}_{i}^{n} + \mathbf{M}_{i}^{**} \right)$

is realizable because RHS are all convex sums of realizable moments

• In general, explicit, high-order, strong stability-preserving schemes are realizable

# Achieve high-order in space and time on unstructured grids!



# 1-D Particle Trajectory Crossing: Main Program I

Computational Models for Polydisperse Particulate and Multiphase Systems

Rodney O. Fox International Francqui Professor

**OBMM** for Spatially Inhomogeneous Systems Inhomogeneous PRF Multivariate OBMM Multidimensional Inversion Algorithms Hyperbolic QMOM High-Order, Realizable. Kinetic-Based. Finite-Volume Methods Kinetic-Based **Finite-Volume** 

Finite-Volume Method Realizable Schemes

Particle Trajectory Crossing

#### Matlab Script for 1-D PTC: $\partial_t \mathbf{M} + \partial_x \mathbf{F} = 0$

```
% Initializing numerical parameters
%
cfl = 0.9 :
Nv = 402 :
TQ = 1:
Lv = 1 : % dimensionless width of domain
H = Ly ; % width of domain (dimensionless units)
Tmax = 1 : % final time
Dv = H/(Nv-2) : % cell size
eps = 1.d-6:
Ycell = -(Dv/2) : Dv : (H+Dv/2) : % grid cell centers
%
% Initializing the cell values
M0 = zeros(5,Ny); % moments
NO = O^{*}ones(4, Ny); % weights
U0 = zeros(4.Nv) : % U velocity
N1 = N0:
U1 = U0:
%
% initial two waves in x direction
for i = 1:48
   NO(1.i) = 1:
   UQ(1,i) = 1:
                                                イロト イポト イヨト イヨト
```



Computational Models for

> Multiphase Systems

Francoui

Professor

**OBMM** for Spatially

Systems

Inhomogeneous PRF

Multidimensional

High-Order,

Realizable.

Methods

Crossing

Kinetic-Based. Finite-Volume

Kinetic-Rased

Finite-Volume Method

## 1-D Particle Trajectory Crossing: Main Program II

```
end
 Polydisperse
             for i = Ny-47:Ny
Particulate and
                 NO(1,i) = 1;
                 UO(1,i) = -1;
Rodney O. Fox
              end
 International
             %
             for i =1:Ny
                 MO(:,i) = moments 4node 5mom(NO(:,i),UO(:,i)) :
                 [N1(:,i),U1(:,i)] = four_node_flux_hygmom(MO(:,i));
              end
Inhomogeneous
             M0(:,1) = moments_4node_5mom(N0(:,Ny-1),U0(:,Ny-1)) ;
             MO(:,Ny) = moments_4node_5mom(NO(:,2),UO(:,2));
              [N1(:,1),U1(:,1)] = four node flux hypmom(MO(:,1)) :
Multivariate OBMM
              [N1(:,Ny),U1(:,Ny)] = four_node_flux_hygmom(M0(:,Ny));
             %
Inversion Algorithms
             M1 = M0 :
Hyperbolic QMOM
             %
             % Time loop
             t = 0:
             while( t < Tmax + eps )</pre>
                 Umax = 0.01 :
Bealizable Schemes
                 for i=1:4
Particle Trajectory
                                                         イロト イボト イヨト イヨト
```

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### 1-D Particle Trajectory Crossing: Main Program III

Computational Models for Polydisperse Particulate and Multiphase Systems

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Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume Method Bealizable Schemes

Particle Trajectory

Crossing

```
for i=1:Nv
        Umax = max(Umax.abs(UO(i.i))) :
    end
end
Dt = cfl*Dv/Umax :
t = t + Dt:
%
% Evaluation of the new moments using RK2SSP
% Step 1 du RK2SSP
%
% Step of spatial transport
for i=2:Nv-1
    % Etape 1
    Nlmoins = NO(:, i-1);
    Ulmoins = U0(:,i-1);
    Nlplus = NQ(:.i)
    Ulplus = UQ(:,i)
    Nrmoins = NQ(:.i)
    Urmoins = UQ(:.i)
    Nrplus = NQ(:,i+1)
    Urplus = UQ(:.i+1) :
    %
    Fleft = flux_5mom(Nlmoins,Ulmoins,Nlplus,Ulplus);
    Fright = flux 5mom(Nrmoins.Urmoins.Nrplus.Urplus):
```



### 1-D Particle Trajectory Crossing: Main Program IV

Computational Models for Polydisperse Particulate and Multiphase Systems

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Kinetic-Based Finite-Volume Methods Kinetic-Based

Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

```
% update moments by time step
    M1(:,i) = M0(:,i) - (Dt/Dy)*(Fright - Fleft) ;
end
% update weights and abscissas
for i=2:Nv-1
    [N1(:,i),U1(:,i)] = four_node_flux_hygmom(M1(:,i)) ;
    M1(:,i) = moments_4node_5mom(N1(:,i),U1(:,i)) ; % projection step
end
M1(:,1) = moments_4node_5mom(N1(:,Ny-1),U1(:,Ny-1)) ;
M1(:.Nv) = moments 4node 5mom(N1(:.2),U1(:.2)) :
[N1(:.1), U1(:.1)] = four node flux hyamom(M1(:.1)) :
[N1(:,Ny),U1(:,Ny)] = four_node_flux_hygmom(M1(:,Ny));
%
% Step 2 du RK2SSP: M0 are old values, M1 are new values
% Step of spatial transport
for i=2:Nv-1
    Nlmoins = N1(:,i-1);
    Ulmoins = U1(:,i-1):
    Nlplus = N1(:.i)
    Ulplus = U1(:,i)
    Nrmoins = N1(:.i)
    Urmoins = U1(:.i)
    Nrplus = N1(:,i+1)
    Urplus = U1(:.i+1):
```



## 1-D Particle Trajectory Crossing: Main Program V

Computational Models for Polydisperse Particulate and Multiphase Systems

%

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Methods Kinetic-Based Finite-Volume Method Bealizable Schemes

end

Particle Trajectory Crossing

```
Fleft = flux_5mom(Nlmoins,Ulmoins,Nlplus,Ulplus);
    Fright = flux 5mom(Nrmoins.Urmoins.Nrplus.Urplus):
    %
    % update moments by full time step
    M1(:,i) = M1(:,i) - (Dt/Dy)*(Fright - Fleft) ;
    M1(:,i) = 0.5*(M0(:,i) + M1(:,i));
end
% update weights and abscissas
for i=2:Nv-1
    [N1(:,i),U1(:,i)] = four_node_flux_hygmom(M1(:,i));
    M1(:.i) = moments 4node 5mom((N1(:.i),U1(:.i)) : % projection step
end
M1(:.1) = moments 4node 5mom(N1(:.Nv-1).U1(:.Nv-1)) :
M1(:.Nv) = moments 4node 5mom(N1(:.2),U1(:.2)) :
[N1(:,1),U1(:,1)] = four_node_flux_hygmom(M1(:,1)) ;
[N1(:.Nv).U1(:.Nv)] = four node flux hvgmom(M1(:.Nv)) :
%
% End of RK2SSP time step
MQ = M1 :
NQ = N1:
UQ = U1:
```



# 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program I

Computational Models for Polydisperse Particulate and Multiphase Systems

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume Method Realizable Schemes

Particle Trajectory Crossing

#### Matlab Script for 1-D PTC: $M \Longrightarrow N, U$ kinetic based

```
function [N, U] = four node flux hyperon (M)
% [ N, U ] = four_node_flux_hygmom( M )
% four-node flux-based HyQMOM with realizability checking
%
% input: 5 velocity moments (in this order)
\% M = [m0, m1, m2, m3, m4]
%
% output:
\% N = [ n1. n2. n3. n4 ] weights
% U = [u1, u2, u3, u4] abscissas (eigenvalues)
%
m0 = M(1); m1 = M(2); m2 = M(3); m3 = M(4); m4 = M(5);
%
%
if isnan(m0) == 1
    display(M)
    error('corrupted moments in four node flux hyamom')
end
%
etasmall = 1.d-10 : % smallest variance for computing eta
verysmall = 1.d-14 ; % smallest nonzero mass
gmax = 30 ; % maximum normalized skewness
% check for zero density
                                                 イロト イポト イヨト イヨト
```

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## 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program II

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based

Finite-Volume Method

Realizable Schemes Particle Trajectory

Crossing

```
N = zeros(4,1); U = N;
if m0 <= verysmall</pre>
    N(1:4) = m0/4:
    return
end
% mean velocities
bu = m1/m0;
% normalized moments
d2 = m2/m0 :
d3 = m3/m0 :
d4 = m4/m0 :
% central moments
c^2 = d^2 - bu^2 :
c_3 = d_3 - 3*bu*d_2 + 2*bu^3:
c4 = d4 - 4*bu*d3 + 6*bu^2*d2 - 3*bu^4:
%
% realizability check
realizable = c2*c4 - c2^3 - c3^2:
if c_2 < 0 % negative variance
    if c2 < - vervsmall
        warning('c2 negative in four_node_flux_hygmom')
        displav(c2)
    end
    c_2 = 0 :
```

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## 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program III

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Methods Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

```
c_{3} = 0:
   c4 = 0:
elseif realizable < 0 % eta < 1 + q<sup>2</sup>
   if c_2 \ge etasmall
        q = c3/sqrt(c2)/c2 : eta = c4/c2/c2 :
        if abs(q) > verysmall
            slope = (eta - 3)/q;
            det = 8 + slope^2 :
            qp = 0.5*(slope + sqrt(det));
            am = 0.5*(slope - sart(det)):
            if sign(q) == 1
                a = ap:
            else
                q = qm:
            end
        else
            a = 0:
        end
        eta = q^{2} + 1:
        c3 = q*sqrt(c2)*c2;
        c4 = eta*c2^{2} :
        if realizable < - 1.d-6
            warning('c4 too small in four_node_flux_hygmom')
            displav(realizable)
```



# 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program IV

Computational Models for Polydisperse Particulate and Multiphase Systems

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume Method Realizable Schemes

Particle Trajectory Crossing

```
display(M)
        end
    else
        c_{3} = 0 :
        c4 = c2^2 :
    end
end
%
% HyQMOM parameters (scaled)
scale = sgrt(c2) :
if c_2 \ge etasmall
    a = c3/sart(c2)/c2:
    eta = c4/c2/c2 :
else
    q = 0; eta = 1;
end
% bound skewness < gmax
if q^2 > qmax^2
    slope = (eta - 3)/q : % move towards Gaussian moments
    q = qmax*sign(q);
    eta = 3 + slope*q:
    realizable = eta - 1 - q^2 :
    if realizable < 0
        eta = 1 + q^2 :
```



# 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program V

Computational Models for Polydisperse Particulate and Multiphase Systems

end

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume

Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

```
end
% compute weights & abscissas (eigenvalues)
if eta > 1 + \alpha^2
   up = zeros(1.4) :
   up(1) = 0.5*(q + sqrt(4*eta - 3*q^2 + 4*sqrt((eta - q^2)*(eta - q^2 - 1))));
    up(2) = 0.5*(q + sqrt(4*eta - 3*q^2 - 4*sqrt((eta - q^2)*(eta - q^2 - 1))));
    up(3) = 0.5*(q - sqrt(4*eta - 3*q^2 - 4*sqrt((eta - q^2)*(eta - q^2 - 1)))):
   up(4) = 0.5*(q - sqrt(4*eta - 3*q^2 + 4*sqrt((eta - q^2)*(eta - q^2 - 1))));
   A = [up : up.^2 : up.^3 : up.^4]
   b = [0 \ 1 \ q \ eta]':
   rho = A h :
else % eta = 1 + q^2
    rho = zeros(4,1);
   dm = sqrt(4*eta - 3*q^2);
   rho(1) = 1/(dm + q)/dm:
   rho(2) = rho(1) :
   rho(3) = 1/(dm - q)/dm;
   rho(4) = rho(3):
   up = zeros(4.1) :
   up(1) = 0.5*(a + dm):
   up(2) = up(1):
   up(3) = 0.5*(q - dm);
   up(4) = up(3):
```


## 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program VI

Computational Models for Polydisperse Particulate and Multiphase Systems

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume Method Realizable Schemes Particle Trajectory

Crossing

%

end % % error checking if max(isnan(rho)) == 1 || max(isnan(up)) == 1 display(rho) displav(up) error('corrupted moments in HvOMOM') end if min(rho) < 0format long display(rho) displav(c2) display(q) display(eta) warning('negative weight in HvOMOM') format short end % N(1) = rho(1): N(2) = rho(2) : N(3) = rho(3); N(4) = rho(4); N = m0\*N :

4 D b 4 B b 4 B b 4 B b



## 1-D Particle Trajectory Crossing: Kinetic-Based HyQMOM Program VII

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

U(1) = scale\*up(1);U(2) = scale\*up(2);U(3) = scale\*up(3):U(4) = scale\*up(4);U = bu + U: % % check moment error m00 = sum(N) : m1o = sum(N.\*U) :  $m_{20} = sum(N, *U, 2)$ :  $m_{30} = sum(N, *U, ^3)$  :  $m40 = sum(N,*U,^4)$ : Mout = [m0o m1o m2o m3o m4o]; err = Mout - M : if err(3) > 1.d-6 && m0 > verysmalldisplav(err) display(M) end % end



## 1-D Particle Trajectory Crossing: Moment Program I

#### Computational Models for Polydisperse Particulate and Multiphase Systems

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

#### Matlab Script for 1-D PTC: $N, U \Longrightarrow M$ kinetic based

```
function mom = moments 4node 5mom(n,u)
% moments from four-node, kinetic-based HyQMOM weights and abscissas
%
% input:
\% N = [ n1. n2. n3. n4] weights
\% U = [ u1. u2. u3. u4] abscissas
%
% output: 5 velocity moments (in this order)
\% M = [m0, m1, m2, m3, m4]
%
mom = zeros(5.1) :
k = [0 \ 1 \ 2 \ 3 \ 4]:
for i = 1:5 % moments number
    for i = 1:4 % node number
        mom(i) = mom(i) + n(j)*u(j)^k(i);
    end
end
end
```

4 D b 4 B b 4 B b 4 B b



## 1-D Particle Trajectory Crossing: Kinetic-Based Flux Program I

Computational Models for Polydisperse Particulate and Multiphase Systems

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods Kinetic-Based Finite-Volume

Method Realizable Schemes

Particle Trajectory Crossing

### Matlab Script for 1-D PTC: $\mathbf{N}_l, \mathbf{U}_l | \mathbf{N}_r, \mathbf{U}_r \Longrightarrow \mathbf{F}$

```
function F = flux 5mom(Nl.Ul.Nr.Ur)
% HyQMOM kinetic-based flux across cell face
%
% input:
% Nl = [n1, n2, n3, n4] left weights
% Ul = [u1, u2, u3, u4] left abscissas
% Nr = [n1, n2, n3, n4] right weights
% Ur = [u1, u2, u3, u4] right abscissas
%
% output: Net flux of moments across cell face
% F = [ F0. F1. F2. F3. F4]
%
F = zeros(5,1);
k = [0 \ 1 \ 2 \ 3 \ 4]:
for i = 1:5 % moments number
    for i = 1:4 % nodes number
        F(i) = F(i) + Nl(i)*Ul(i)^k(i) * max(Ul(i).0) ...
                    + Nr(j)*Ur(j)^k(i) * min(Ur(j),0) ;
    end
end
end
```



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QBMM for Spatially Inhomogeneous Systems

PBE

Multivariate QBMM

Multidimensional Inversion Algorithms

Hyperbolic QMOM

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Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 1-D

Uncorrelated moments

Loading movie...

### 16-moment, 27-node CHyQMOM

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High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

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Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 1-D

#### Quadrature weights and abscissas

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### 16-moment, 27-node CHyQMOM

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Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 1-D

#### Perfectly correlated moments

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### 16-moment, 27-node CHyQMOM

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Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

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Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 1-D

#### Quadrature weights and abscissas

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### 16-moment, 27-node CHyQMOM

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PBE

Multivariate QBMM

Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 1-D

#### Partially correlated moments

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### 16-moment, 27-node CHyQMOM



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PBE

Multivariate QBMM

Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 1-D

#### Quadrature weights and abscissas

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### 16-moment, 27-node CHyQMOM

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Inhomogeneous PBE

Multivariate QBMM

Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory

Crossing

## Particle Trajectory Crossing in 2-D

Loading movie...

### 10-moment, 9-node CHyQMOM

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QBMM for Spatially Inhomogeneous Systems

Inhomogeneous PBE

Multivariate QBMM

Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

## Particle Trajectory Crossing in 3-D

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### 16-moment, 27-node CHyQMOM

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Computational Models for Polydisperse Particulate and Multiphase Systems

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QBMM for Spatially Inhomogeneous Systems

Inhomogeneous PBE

Multivariate QBMM Multidimensional Inversion Algorithms

Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing • When solving moment transport equations, we must guarantee realizability!

First-order FV methods are realizable, but too diffusive

• Standard high-order FV methods lead to **unrealizable moments!** 

• Kinetic-based flux functions can be designed to be realizable

• Use **quadrature representation** (e.g. HyQMOM) with high-order spatial reconstruction of weights

• High-order time-stepping schemes are also possible

• KBFVM provide robust treatment of shocks/discontinuous solutions on unstructured grids



Computational Models for Polydisperse Particulate and Multiphase Systems

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QBMM for Spatially Inhomogeneous Systems

Inhomogeneous PBE

Multivariate QBMM Multidimensional

Inversion Algorithms Hyperbolic QMOM

High-Order, Realizable, Kinetic-Based, Finite-Volume Methods

Kinetic-Based Finite-Volume Method

Realizable Schemes Particle Trajectory Crossing

- When solving moment transport equations, we must guarantee realizability!
- First-order FV methods are realizable, but too diffusive
- Standard high-order FV methods lead to **unrealizable** moments!
- Kinetic-based flux functions can be designed to be realizable
- Use **quadrature representation** (e.g. HyQMOM) with high-order spatial reconstruction of weights
- High-order time-stepping schemes are also possible
- KBFVM provide robust treatment of shocks/discontinuous solutions on unstructured grids



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### Part 5

Computational Models for Polydisperse Particulate and Multiphase Systems

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Application to Fine-Particle Formation

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Flame Synthesis of Nanoparticles LES Results

Application to Bubbly Flows

QBMM for Bubble Columns

Flows with Coalescence and Breakage

Simulation of Stirred Tanks with QBMM

## APPLICATION TO FINE-PARTICLE FORMATION

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Computational Models for Polydisperse Particulate and

Multiphase Systems Rodney O. Fox International

Francoui

Professor

Modeling Approach

Flame Synthesis of

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Bubbly Flows QBMM for Bubble Columns Flows with

Coalescence and Breakage Simulation of Stirred Tanks with OBMM

Application to

**Fine-Particle** 

Formation

## Nanoparticles in Turbulent Mixers

Flash Nanoprecipitation



#### Produced in Multi-Inlet Vortex Reactor

Model needed for turbulent mixing and PBE

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## Nanoparticles in Turbulent Flames

Computational Models for Polydisperse Particulate and Multiphase Systems

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#### Soot



### Metal oxides



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(Strobel & Pratsinis 2007)

### Model needed for turbulent combustion and PBE

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## **Computational Model**

Computational Models for Polydisperse Particulate and Multiphase Systems

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### Part. size dist. (PSD)

- PBE
  - Solve for NDF *n*(*v*)
  - Coupled to velocity, reactive scalars
  - Non-linear integro-PDE
- QBMM
  - Solve for moments of NDF
  - Close by reconstructing n(v)



Computational Models for Polydisperse Particulate and Multiphase Systems



Computational Models for Polydisperse

> Multiphase Systems

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Tanks with OBMM

## Quadrature-Based Moment Methods



Close moment equations by reconstructing density function



## Flame Synthesis of Metal-Oxide Nanoparticles

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- Flamelet model for turbulent combustion
- QBMM for volume–surface NDF n(v, a)
- PBE accounts for nucleation, growth, aggregation, and sintering



## **Bivariate Population Balance Equation**

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$$\frac{\partial n(v,a)}{\partial t} + \nabla_{\mathbf{x}} \cdot \mathbf{U}_{g} n(v,a) + \frac{\partial G_{v}(v,a)n(v,a)}{\partial v} + \frac{\partial G_{a}(v,a)n(v,a)}{\partial a} + \frac{\partial S_{a}(v,a)n(v,a)}{\partial a} = J(T,\phi)\delta(v-v_{0})\delta(a-a_{0}) + B(v,a) - D(v,a)$$

- $G_{v}$ ,  $G_{a}$ : surface growth rates of volume and surface area
- S<sub>a</sub>: rate of change of surface area due to sintering
- J: nucleation rate of particles volume  $v_0$  and surface area  $a_0$
- Aggregation birth and death terms:

$$B = \frac{1}{2} \int_0^a \int_0^v \beta(v - v^*, v^*, a - a^*, a^*) n(v - v^*, a - a^*) n(v^*, a^*) \, \mathrm{d}v^* \, \mathrm{d}a^*$$
$$D = \int_0^\infty \int_0^\infty \beta(v, v^*, a, a^*) n(v, a) n(v^*, a^*) \, \mathrm{d}v^* \, \mathrm{d}a^*$$



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Simulation of Stirred Tanks with QBMM • Nucleation:  $k_{\text{nucl}} = 10^{13} \text{ (cm}^6/\text{mol}^2\text{s})$ 

 $J(T,\phi) = k_{\text{nucl}} N_{\text{av}} [\text{Ti}_5 \text{O}_6 \text{CI}_8] [\text{O}_2]^2$ 

$$v_0 = 16.6 \times 10^{-29} \text{ m}^3$$
,  $a_0 = 14.6 \times 10^{-19} \text{ m}^2$ 

• Surface growth  $k_s = 49 \exp(-8993/T)$  (m/s)

 $G_{v}(v, a) = k_{s}[\text{TiCl}_{4}]N_{av}v_{0}a$ 

$$G_a(v, a) = 4k_s[\text{TiCl}_4]N_{av}v_0\sqrt{\pi a}$$

Nav is Avagadro's number

Gas-phase species found from detailed combustion model for TiCl<sub>4</sub>



Sintering

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$$S_{a}(v,a) = \begin{cases} \frac{(a-a_{s})}{\tau_{t}(d_{p}^{*})} & \text{if } n_{p} \leq 2\\ (n_{p}-1)\left(\frac{0.41a_{p}}{\tau_{t}(d_{p})}\right) & \text{if } n_{p} > 2 \end{cases}$$
$$a_{s} = (36\pi v^{2})^{1/3}, d_{p}^{*} = (3v/\pi)^{1/3}, d_{p} = 6v/a, a_{p} = 36\pi v^{2}/a^{2},$$
$$n_{p} = a^{3}/(36\pi v^{2})$$

Sintering time scale

$$\tau_{\rm f}(x) = k_0 x^m \frac{T}{T_0} \exp\left[\frac{E_{\rm a}}{R} \left(\frac{1}{T} - \frac{1}{T_0}\right)\right]$$

 $k_0 = 1 \times 10^{28} \text{ m}^{-4}$ ,  $T_0 = 1400 \text{ K}$ , m = 4,  $E_a = 1.5 \times 10^5 \text{ J/mol}$ 



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#### Aggregation kernel

$$\beta(v, a, v^*, a^*) = \frac{2RT}{3\mu N_{\mathsf{a}v}} \left(\frac{1}{v^{1/d_{\mathfrak{f}}}} + \frac{1}{v^{*1/d_{\mathfrak{f}}}}\right) \left(v^{1/d_{\mathfrak{f}}} + v^{*1/d_{\mathfrak{f}}}\right)$$

 $\mu$  gas viscosity,  $d_{\rm f}(v, a)$  fractal dimension ( $\approx 2.5$ )

Models lead to stiff equations that are strongly coupled to gas-phase chemistry and temperature!



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Simulation of Stirred Tanks with QBMM Moments of NDF are defined by

$$m_{k,l} = \int_0^\infty \int_0^\infty a^l v^k n(v,a) \, \mathrm{d}v \, \mathrm{d}a$$

• Transport equation for moment  $m_{k,l}$  is found from PBE using

$$\int_0^\infty \int_0^\infty a^l v^k [\mathsf{PBE}] \, \mathrm{d} v \, \mathrm{d} a$$

#### • Accumulation term:

$$\int_0^\infty \int_0^\infty a^l v^k \frac{\partial n(v,a)}{\partial t} \, \mathrm{d}v \, \mathrm{d}a = \frac{\partial}{\partial t} \int_0^\infty \int_0^\infty a^l v^k n(v,a) \, \mathrm{d}v \, \mathrm{d}a = \frac{\partial m_{k,l}}{\partial t}$$

• Advection term:

$$\int_0^\infty \int_0^\infty a^l v^k \nabla_{\mathbf{x}} \cdot \mathbf{U}_g n(v, a) \, \mathrm{d}v \, \mathrm{d}a = \nabla_{\mathbf{x}} \cdot \mathbf{U}_g m_{k, q}$$

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Volume growth term:

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# $\int_0^\infty \left( \int_0^\infty v^k \frac{\partial}{\partial v} [G_v(v,a)n(v,a)] \, \mathrm{d}v \right) a^l \, \mathrm{d}a$ = $\int_0^\infty \left[ v^k G_v(v,a)n(v,a) \Big|_0^\infty - \int_0^\infty k v^{k-1} G_v(v,a)n(v,a) \, \mathrm{d}v \right] a^l \, \mathrm{d}a$

• after integration by parts and  $0 \le G_v$ 

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial v} [G_v(v,a)n(v,a)] dv da$$

$$-\int_0^\infty \int_0^\infty kv^{k-1}a^l G_v(v,a)n(v,a)dvda$$

• Surface area growth term:

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial a} [G_a(v,a)n(v,a)] \, \mathrm{d}v \, \mathrm{d}a$$

 $= -\int_{0}^{\infty}\int_{0}^{\infty} lv^{k}a^{l-1}G_{a}(v,a)n(v,a) \,\mathrm{d}v \,\mathrm{d}a$   $(a \to b \in \mathbb{D} \times (\mathbb{D} \times (\mathbb{D} \times \mathbb{D} \times \mathbb{D}$


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• Volume growth term:

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$$= \int_0^\infty \left[ v^k G_v(v, a)n(v, a) \Big|_0^\infty - \int_0^\infty k v^{k-1} G_v(v, a)n(v, a) \, \mathrm{d}v \right] a^l \, \mathrm{d}a$$

• after integration by parts and  $0 \le G_v$ 

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial v} [G_v(v,a)n(v,a)] dv da$$
$$= -\int_0^\infty \int_0^\infty k v^{k-1} a^l G_v(v,a)n(v,a) dv da$$

• Surface area growth term:

 $= -\int_{0}^{\infty} \int_{0}^{\infty} lv^{k} a^{l-1} G_{a}(v, a) n(v, a) \, \mathrm{d}v \, \mathrm{d}a$   $( \Box \mapsto \langle \Box \rangle \langle \Box \rangle \langle \Box \rangle \langle \Box \rangle \rangle \langle \Box \rangle \langle \Box$ 



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$$= \int_0^\infty \left[ v^k G_v(v,a)n(v,a) \Big|_0^\infty - \int_0^\infty k v^{k-1} G_v(v,a)n(v,a) \, \mathrm{d}v \right] a^l \, \mathrm{d}a$$

• after integration by parts and  $0 \le G_v$ 

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial v} [G_v(v, a)n(v, a)] dv da$$
$$= -\int_0^\infty \int_0^\infty k v^{k-1} a^l G_v(v, a)n(v, a) dv da$$

• Surface area growth term:

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial a} [G_a(v, a)n(v, a)] \, \mathrm{d}v \, \mathrm{d}a$$
$$= -\int_0^\infty \int_0^\infty h v^k a^{l-1} G_a(v, a)n(v, a) \, \mathrm{d}v \, \mathrm{d}a$$



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$$\int_0^\infty \left( \int_0^\infty a^l \frac{\partial}{\partial a} [S_a(v, a)n(v, a)] \, \mathrm{d}a \right) v^k \, \mathrm{d}v$$
$$= \int_0^\infty \left[ a^l S_a(v, a)n(v, a) \Big|_0^\infty - \int_0^\infty l a^{l-1} S_a(v, a)n(v, a) \, \mathrm{d}v \right] v^k \, \mathrm{d}a$$

after integration by parts

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial a} [S_a(v,a)n(v,a)] \, \mathrm{d}v \, \mathrm{d}a$$

$$= -\int_0 \int_0 lv^k a^{l-1} S_a(v, a) n(v, a) \,\mathrm{d}v \,\mathrm{d}a$$

• Nucleation term:

Sintering term:

$$\int_0^\infty \int_0^\infty J(T,\phi)\delta(v-v_0)\delta(a-a_0)a^lv^k\,\mathrm{d}v\,\mathrm{d}a = J(T,\phi)v_0^ka_0^l$$



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#### • Sintering term:

$$\int_0^\infty \left( \int_0^\infty a^l \frac{\partial}{\partial a} [S_a(v, a)n(v, a)] \, \mathrm{d}a \right) v^k \, \mathrm{d}v$$
  
= 
$$\int_0^\infty \left[ a^l S_a(v, a)n(v, a) \Big|_0^\infty - \int_0^\infty l a^{l-1} S_a(v, a)n(v, a) \, \mathrm{d}v \right] v^k \, \mathrm{d}a$$

• after integration by parts

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial a} [S_a(v, a)n(v, a)] \, \mathrm{d}v \, \mathrm{d}a$$
$$= -\int_0^\infty \int_0^\infty l v^k a^{l-1} S_a(v, a)n(v, a) \, \mathrm{d}v \, \mathrm{d}a$$

• Nucleation term:

$$\int_0^\infty \int_0^\infty J(T,\phi)\delta(v-v_0)\delta(a-a_0)a^lv^k\,\mathrm{d}v\,\mathrm{d}a = J(T,\phi)v_0^ka_0^l$$



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after integration by parts

$$\int_0^\infty \int_0^\infty v^k a^l \frac{\partial}{\partial a} [S_a(v, a)n(v, a)] \, \mathrm{d}v \, \mathrm{d}a$$
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#### • Aggregation birth term:

$$\begin{split} &\int_0^\infty \int_0^\infty v^k a^l B(v,a) \, \mathrm{d}v \, \mathrm{d}a \\ &= \frac{1}{2} \int_0^\infty a^l \int_0^a \left[ \int_0^\infty \int_0^v \beta(v-v^*,v^*,a-a^*,a^*) n(v-v^*,a-a^*) n(v^*,a^*) \, \mathrm{d}v^* v^k \, \mathrm{d}v \right] \mathrm{d}a^* \, \mathrm{d}a \end{split}$$

#### • change in order of integration

$$=\frac{1}{2}\int_0^\infty a^l \int_0^a \left[\int_0^\infty \int_{v^*}^\infty \beta(v-v^*,v^*,a-a^*,a^*)n(v-v^*,a-a^*)v^k \,\mathrm{d}v \, n(v^*,a^*) \,\mathrm{d}v^*\right] \,\mathrm{d}a^* \,\mathrm{d}a$$

• change of variables  $v' = v - v^*$ 

$$= \frac{1}{2} \int_0^\infty a^l \int_0^a \left[ \int_0^\infty \int_0^\infty \beta(v', v^*, a - a^*, a^*) n(v', a - a^*) (v' + v^*)^k \, \mathrm{d}v' n(v^*, a^*) \, \mathrm{d}v^* \right] \, \mathrm{d}a^* \, \mathrm{d}a$$



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• change of variables 
$$v' = v - v^*$$

$$= \frac{1}{2} \int_0^\infty a^l \int_0^a \left[ \int_0^\infty \int_0^\infty \beta(v', v^*, a - a^*, a^*) n(v', a - a^*)(v' + v^*)^k \, \mathrm{d}v' n(v^*, a^*) \, \mathrm{d}v^* \right] \mathrm{d}a^* \, \mathrm{d}a$$



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• change of variables  $v' = v - v^*$ 

$$=\frac{1}{2}\int_0^\infty a^l \int_0^a \left[\int_0^\infty \int_0^\infty \beta(v',v^*,a-a^*,a^*)n(v',a-a^*)(v'+v^*)^k \,\mathrm{d}v'n(v^*,a^*) \,\mathrm{d}v^*\right] \mathrm{d}a^* \,\mathrm{d}a$$



same steps for a

 $=\frac{1}{2}\int_0^\infty\int_0^\infty\int_0^\infty\int_0^\infty(v'+v^*)^k(a'+a^*)^l\beta(v',v^*,a',a^*)n(v',a')n(v^*,a^*)\,\mathrm{d}v^*\,\mathrm{d}a^*\,\mathrm{d}v'\,\mathrm{d}a'$ 

combining everything yields

 $\int_{0}^{\infty} \int_{0}^{\infty} v^{k} a^{l} B(v, a) \, dv \, da$ =  $\frac{1}{2} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} (v + v^{*})^{k} (a + a^{*})^{l} \beta(v, v^{*}, a, a^{*}) n(v, a) n(v^{*}, a^{*}) \, dv^{*} \, da^{*} \, dv \, da$ 

• Aggregation death term:  $\beta(v, v^*, a, a^*) = \beta(v^*, v, a^*, a)$ 

 $\int_{0}^{\infty} \int_{0}^{\infty} v^{k} a^{l} D(v, a) \, \mathrm{d}v \, \mathrm{d}a$ =  $\frac{1}{2} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} \left( v^{k} a^{l} + v^{*k} a^{*l} \right) \beta(v, v^{*}, a, a^{*}) n(v, a) n(v^{*}, a^{*}) \, \mathrm{d}v^{*} \, \mathrm{d}a^{*} \, \mathrm{d}v \, \mathrm{d}a$ 

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• same steps for a

 $= \frac{1}{2} \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty (v' + v^*)^k (a' + a^*)^l \beta(v', v^*, a', a^*) n(v', a') n(v^*, a^*) \, \mathrm{d} v^* \, \mathrm{d} a^* \, \mathrm{d} v' \, \mathrm{d} a'$ 

combining everything yields

$$\begin{split} &\int_0^\infty \int_0^\infty v^k a^l B(v,a) \, \mathrm{d}v \, \mathrm{d}a \\ &= \frac{1}{2} \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty (v+v^*)^k (a+a^*)^l \beta(v,v^*,a,a^*) n(v,a) n(v^*,a^*) \, \mathrm{d}v^* \, \mathrm{d}a^* \, \mathrm{d}v \, \mathrm{d}a \end{split}$$

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$$\int_0^\infty \int_0^\infty v^k a^l B(v, a) \, \mathrm{d}v \, \mathrm{d}a$$
  
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 $=\frac{1}{2}\int_0^\infty\int_0^\infty\int_0^\infty\int_0^\infty(v'+v^*)^k(a'+a^*)^l\beta(v',v^*,a',a^*)n(v',a')n(v^*,a^*)\,\mathrm{d}v^*\,\mathrm{d}a^*\,\mathrm{d}v'\,\mathrm{d}a'$ 

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same steps for a

 $= \frac{1}{2} \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty (v' + v^*)^k (a' + a^*)^l \beta(v', v^*, a', a^*) n(v', a') n(v^*, a^*) \, \mathrm{d} v^* \, \mathrm{d} a^* \, \mathrm{d} v' \, \mathrm{d} a'$ 

combining everything yields

$$\int_0^\infty \int_0^\infty v^k a^l B(v, a) \, \mathrm{d}v \, \mathrm{d}a$$
  
=  $\frac{1}{2} \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty (v + v^*)^k (a + a^*)^l \beta(v, v^*, a, a^*) n(v, a) n(v^*, a^*) \, \mathrm{d}v^* \, \mathrm{d}a^* \, \mathrm{d}v \, \mathrm{d}a$ 

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$$\begin{split} \int_0^\infty \int_0^\infty v^k a^l D(v, a) \, \mathrm{d}v \, \mathrm{d}a \\ &= \frac{1}{2} \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty \left( v^k a^l + v^{*k} a^{*l} \right) \beta(v, v^*, a, a^*) n(v, a) n(v^*, a^*) \, \mathrm{d}v^* \, \mathrm{d}a^* \, \mathrm{d}v \, \mathrm{d}a \end{split}$$

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Final result:

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**OBMM** for Bubble Columns

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Simulation of Stirred Tanks with OBMM

$$\begin{aligned} \frac{\partial m_{k,l}}{\partial t} + \nabla_{\mathbf{x}} \cdot \mathbf{U}_{g} m_{k,l} &= \\ & J(T,\phi) v_{0}^{k} a_{0}^{l} + \int_{0}^{\infty} \int_{0}^{\infty} k v^{k-1} a^{l} G_{v}(v,a) \, \mathbf{n}(v,a) \, \mathrm{d}v \, \mathrm{d}a \\ & + \int_{0}^{\infty} \int_{0}^{\infty} l v^{k} a^{l-1} \left[ G_{a}(v,a) + S_{a}(v,a) \right] \mathbf{n}(v,a) \, \mathrm{d}v \, \mathrm{d}a \\ & + \frac{1}{2} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} \int_{0}^{\infty} \left[ (v + v^{*})^{k} (a + a^{*})^{l} - v^{k} a^{l} - v^{*k} a^{*l} \right] \\ & \beta(v, v^{*}, a, a^{*}) \, \mathbf{n}(v, a) \, \mathbf{n}(v^{*}, a^{*}) \, \mathrm{d}v^{*} \, \mathrm{d}a^{*} \, \mathrm{d}v \, \mathrm{d}a \end{aligned}$$

where  $\mathbf{U}_{g}$  is gas-phase velocity from flow code

### QBMM are needed to close the RHS



## Application of CQMOM to Moments

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Simulation of Stirred Tanks with QBMM Reconstructed NDF:  $N_v = N_a = 3$ 

$$n^{*}(v,a) = \sum_{i=1}^{N_{v}} \sum_{j=1}^{N_{a}} w_{i,j} \delta(v - v_{i}) \delta(a - a_{i,j})$$

CQMOM approximation for 21 moments:

$$m_{k,l} = \sum_{i=1}^{N_v} \sum_{j=1}^{N_a} w_{i,j} v_i^k a_{i,j}^l$$

				$m_{0,4}$		
				$m_{1,4}$		
				$m_{2,4}$		
	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	
						$\rightarrow \{w_{1,j}, a_{1,j}\}$
						$\rightarrow \{w_{2,j}, a_{2,j}\}$
$\downarrow$						$\rightarrow \{w_{3,j}, a_{3,j}\}$

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CQMOM approximation for 21 moments:

$$m_{k,l} = \sum_{i=1}^{N_v} \sum_{j=1}^{N_a} w_{i,j} v_i^k a_{i,j}^l$$

$m_{0,0}$	$m_{0,1}$	$m_{0,2}$	$m_{0,3}$	$m_{0,4}$	$m_{0,5}$	
$m_{1,0}$	$m_{1,1}$	$m_{1,2}$	$m_{1,3}$	$m_{1,4}$	$m_{1,5}$	
$m_{2,0}$	$m_{2,1}$	$m_{2,2}$	$m_{2,3}$	$m_{2,4}$	$m_{2,5}$	
$m_{3,0}$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	
$m_{4,0}$	$\langle a \rangle_1$	$\langle a^2 \rangle_1$	$\langle a^3 \rangle_1$	$\langle a^4 \rangle_1$	$\langle a^5 \rangle_1$	$\rightarrow \{w_{1,j}, a_{1,j}\}$
$m_{5,0}$	$\langle a \rangle_2$	$\langle a^2 \rangle_2$	$\langle a^3 \rangle_2$	$\langle a^4 \rangle_2$	$\langle a^5 \rangle_2$	$\rightarrow \{w_{2,j}, a_{2,j}\}$
$\downarrow$	$\langle a \rangle_3$	$\langle a^2 \rangle_3$	$\langle a^3 \rangle_3$	$\langle a^4 \rangle_3$	$\langle a^5 \rangle_3$	$\rightarrow \{w_{3,j}, a_{3,j}\}$
$\{w_i, v_i\}$						

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## Application of CQMOM to Transport Equation

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#### Final result:

$$\begin{aligned} & \frac{\partial m_{k,l}}{\partial t} + \nabla_{\mathbf{x}} \cdot \mathbf{U}_{g} m_{k,l} = J(T, \phi) v_{0}^{k} a_{0}^{l} & \text{nucleation} \\ & + \sum_{i=1}^{N_{v}} \sum_{j=1}^{N_{a}} w_{i,j} k v_{i}^{k-1} a_{i,j}^{l} G_{v}(v_{i}, a_{i,j}) & \text{volume change} \\ & + \sum_{i=1}^{N_{v}} \sum_{j=1}^{N_{a}} w_{i,j} l v_{i}^{k} a_{i,j}^{l-1} \left[ G_{a}(v_{i}, a_{i,j}) + S_{a}(v_{i}, a_{i,j}) \right] & \text{area change} \\ & + \frac{1}{2} \sum_{i=1}^{N_{v}} \sum_{j=1}^{N_{a}} \sum_{m=1}^{N_{v}} \sum_{n=1}^{N_{a}} w_{i,j} w_{m,n} & \text{aggregation} \\ & \left[ (v_{i} + v_{m})^{k} (a_{i,j} + a_{m,n})^{l} - v_{i}^{k} a_{i,j}^{l} - v_{m}^{k} a_{m,n}^{l} \right] \beta(v_{i}, v_{m}, a_{i,j}, a_{m,n}) \end{aligned}$$

### RHS is now closed

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## Implementation in LES code



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- *m*<sub>10</sub> mean particle volume
- m<sub>01</sub> mean particle surface area
- N<sub>pp</sub> primary particles (nuclei)



### Number concentration vs. residence time

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### $d_p$ vs. residence time

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QBMM for Bubble Columns

Flows with Coalescence and Breakage

Simulation of Stirred Tanks with QBMM





### Surface area vs. residence time

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- · Complex flow physics
  - Turbulence in non-canonical geometries
  - Coupling with turbulent mixing and combustion
  - Heat transfer, acoustics, compressible flow

### Complex chemistry

- Non-equilibrium chemistry (rich, lean)
- Premixed/nonpremixed/partially premixed combustion
- Fine particles ('slow' chemistry, high Sc, radiation)
- Fine particle dynamics
  - Particle size/chemical composition distribution
  - Nucleation, oxidation, surface growth
  - Aggregation, coagulation, sintering



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## **APPLICATION TO BUBBLY FLOWS**

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# QBMM for Bubble Flows

Monokinetic assumption

#### Bubble velocity distribution

- Due to  $\rho_g \ll \rho_l$ , bubble have very small Stokes numbers
- In GPBE, bubble velocity is monokinetic:

$$n(\mathbf{v}_p,\xi) = n(\xi)\,\delta\left(\mathbf{v}_p - \mathbf{U}_p(\xi)\right)$$

- In words, bubble velocity depends only on "size" and velocity fluctuations for fixed "size" are negligible
- · However, many forces in addition to drag are needed

#### Moments

- Size moments needed to reconstruct  $n(\xi)$
- Joint size-velocity moments  $\langle \xi^k \mathbf{v}_p \rangle$  needed to approximate  $\mathbf{U}_p(\xi)$

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Geometry description

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#### Rectangular bubble column

- Contaminated air–water
- Superficial gas velocity: 2.4–21.3 m/s
- Exp. measur.: gas hold-up, plume oscillation period (POP), mean Sauter diameter

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Diaz, M.E., Montes, F.J., Galan, M.A., 2008. Chemical Engineering and Processing 47, 1867-1876.



QBMM for Bubble Columns Computational details for OpenFOAM

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- QMOM and CQMOM implemented in OpenFOAM solver compressibleTwoPhaseEulerFoam (two-phase Eulerian-Eulerian equations) with compressibility effects disabled (isothermal system)
- Drag coefficient calculated through terminal velocity (20 cm/s) and other drag correlations but other interfacial forces neglected
- Standard  $k-\varepsilon$  model for liquid turbulence
- PBM solved with QMOM for four moments (M<sub>0</sub>, M<sub>1</sub>, M<sub>2</sub>, M<sub>3</sub>) corresponding to a two-node quadrature and CQMOM for nine moments (M<sub>0,0</sub>, M<sub>1,0</sub>, M<sub>2,0</sub>, M<sub>3,0</sub>, M<sub>4,0</sub>, M<sub>5,0</sub>, M<sub>0,1</sub>, M<sub>1,1</sub>, M<sub>2,1</sub>) corresponding to a three-node quadrature
- Adaptive first-order Euler time discretization scheme with ∆*t* chosen so that CFL condition is respected
- Inlet condition for gas bubbles:  $\alpha_G = 0.5$ ; inlet gas velocity to match gassing rate; lognormal BSD centered on mean size<sup>2</sup>

<sup>&</sup>lt;sup>2</sup>Geary, N.W., Rice, R.G., 1991. AIChE J. 37, 161-168.



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Variable	Scheme	Inlet	Outlet	Wall
Gas vol. frac.	Limited Second Order Upwind	0.5	Gradient zero	Gradient zero
Gas velocity	Limited Second Order Upwind	Dep. on flow rate	Gradient zero with backflow	Free-slip wall
Liquid velocity	Limited Second Order Upwind	0.0 m/s	Gradient zero	No-slip wall
Pressure	First Order Upwind	Gradient zero	1 bar	Gradient zero
k	Limited Second Order Upwind	Based on turb. Int. = 5%	1 · 10 <sup>-4</sup> m <sup>2</sup> s <sup>-2</sup> (backflow only)	Gradient zero
ε	Limited Second Order Upwind	length scale equal to the hole diam.	1 · 10 <sup>-5</sup> m <sup>2</sup> s- <sup>3</sup> (backflow only)	Gradient zero
Moments	First Order Upwind	Log-normal distrib.	Gradient zero	Gradient zero

$$M_k = M_0 \exp\left\{k\mu + \frac{k^2\sigma^2}{2}\right\}, \mu = \log\left(\frac{m^2}{\sqrt{\nu + m^2}}\right)\sigma = \sqrt{\log\left(\frac{\nu}{m^2} + 1\right)}$$
  
Gas vol. frac. =  $k_V M_3 = k_V M_0 \exp\left\{3\mu + \frac{9\sigma^2}{2}\right\}$ 

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#### QBMM for Bubble Columns Grid independence

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Simulation of Stirred Tanks with QBMM Mesh size effect on calculated gas hold-up, Plume Oscillation Period and Sauter Diameter compared with experiments for  $U_G = 2.4$  mm/s

Grid size	Num.	Hold-up	POP (s)	<i>d</i> <sub>32</sub> (mm)
Coarse	5355	0.64%	7.78	5.78
Medium	24640	0.62%	10.57	6.92
Fine	150784	0.57%	11.71	5.93
Experiment		0.69%	11.37	6.83



flow field and gas profile at 2.4 mm/s



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Flow field and gas profile at 11.9 mm/s

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Flow field and gas profile at 21.3 mm/s



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## Results QBMM Mean bubble size

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### QBMM for Bubble Columns Mean bubble size

Models for Effect of inlet mean bubble size Polydisperse Particulate and Multiphase Systems Experim. GR+15% Rodney O. Fox International GR GR-15% Francqui Professor 8 Application to **Fine-Particle** Sauter diameter (mm) Formation Overview of 7 Modeling Approach Flame Synthesis of Nanoparticles LES Results 6 Application to **Bubbly Flows** QBMM for Bubble 5 Flows with Coalescence and Breakage Simulation of Stirred Tanks with OBMM 2.4 11.9 Superficial velocity (mm/s) イロト イロト イヨト イヨト

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# QBMM for Bubble Columns

## Effect of inlet lognormal std deviation



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## QBMM for Bubble Columns Plume oscillation period

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Simulation of Stirred Tanks with QBMM Comparison of experimental data and calculated results for global gas volume fraction (hold-up), POP and mean Sauter diameter varying the superficial gas velocity  $U_G$ 

Superf. vel. (mm/s)	Hold-up	POP (s)	d <sub>32</sub> (mm)
2.4	0.62%	10.10	6.01
Exp.	0.69%	11.37	6.83
7.1	1.61%	8.26	6.28
Exp.	1.81%	5.69	7.05
11.9	2.45%	5.83	6.89
Exp.	2.63%	4.27	6.50
16.6	3.36%	3.80	7.01
Exp.	3.36%	3.01	6.40
21.3	4.19%	3.84	7.96
Exp.	4.10%	2.84	7.73



CQMOM implementation for oxygen transfer



Computational Models for Polydisperse Particulate and Multiphase Systems



CQMOM implementation for oxygen transfer



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- Simulation of Stirred Tanks with QBMM

- Consider a batch homogeneous GAS–LIQUID system (i.e. one isolated cell of computational domain)
  - Gas bubbles are characterized by SIZE (*L*) and by composition through MOLES (φ) of active component
  - Bubbles undergo ONLY coalescence and breakup (no mass transfer)
- Initial condition: bivariate (in size and composition) Gaussian distribution
- There is no flux of bubbles through cell
- Evolution of NDF is predicted with DSMC



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## Coalescence and Breakage

### NDF at steady state for bubble size and concentration



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- Consider one single cell of finite volume code
- Bubble coalescence, breakup, mass transfer, chemical reaction in liquid phase
- Initial condition: bubbles with same concentration and lognormal bubble size distribution
- Constant flux of bubbles enters cell with NDF corresponding to initial condition
- Evolution of NDF is predicted with DSMC



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# Initial NDF and at steady state for bubble size and concentration







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## Comparison DSMC with QBMM

### **CQMOM** with $N_1 = 3$ and $N_2 = 1$ tracking 9 moments of NDF





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## Comparison DSMC with QBMM

### **CQMOM** with $N_1 = 3$ and $N_2 = 2$ tracking 15 moments of NDF





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Coalescence, breakage and mass transfer. Solid black line: DSMC method. Red line CQMOM with  $N_1 = 3$  and  $N_2 = 1$  and DQMOM with N = 3.

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### Mean percentage error of QBMM for examined case at steady state

		<b>M</b> <sub>0,0</sub>	$M_{1,0}$	<b>M</b> <sub>2,0</sub>	<b>M</b> <sub>3,0</sub>	<b>M</b> 4,0	<b>M</b> <sub>5,0</sub>	<b>M</b> 6,0	<b>M</b> 7,0
N	=2	10.1	7.9	4.6	0.5	6.5	22.3	38.3	50.1
N	=3	7.9	5.2	2.3	0.5	3.3	6.2	8.2	6.9
N	=4	7.7	5.1	2.4	0.4	3.3	6.4	9.5	12.7
		<b>M</b> <sub>0,1</sub>	<b>M</b> <sub>1,1</sub>	<b>M</b> <sub>2,1</sub>	<b>M</b> <sub>3,1</sub>				
N	=2	<b>М</b> <sub>0,1</sub> 2.1	<b>M</b> <sub>1,1</sub> 6.5	<b>M</b> <sub>2,1</sub> 21.4	<b>M</b> <sub>3,1</sub> 44.6				
N N	=2 =3	<b>M</b> <sub>0,1</sub> 2.1 1.9	<b>M</b> <sub>1,1</sub> 6.5 1.8	<i>M</i> <sub>2,1</sub> 21.4 4.7	<b>M</b> <sub>3,1</sub> 44.6 6.2				
N N N	=2 =3 =4	<b>M</b> <sub>0,1</sub> 2.1 1.9 3.2	<b>M</b> <sub>1,1</sub> 6.5 1.8 1.7	<b>M</b> <sub>2,1</sub> 21.4 4.7 3.4	<b>M</b> <sub>3,1</sub> 44.6 6.2 6.4				
N N N	=2 =3 =4	<b>M</b> <sub>0,1</sub> 2.1 1.9 3.2	<b>M</b> <sub>1,1</sub> 6.5 1.8 1.7	<b>M</b> <sub>2,1</sub> 21.4 4.7 3.4	<b>M</b> <sub>3,1</sub> 44.6 6.2 6.4				



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#### Application to Fine-Particle Formation

Overview of Modeling Approach

Flame Synthesis of Nanoparticles

### Application to Bubbly Flows

QBMM for Bubble Columns

Flows with Coalescence and Breakage

Simulation of Stirred Tanks with QBMM

- With DSMC evolution of population of bubbles is represented through its stochastic equivalent (with  $N \approx 100$  notional bubbles)
  - With QBMM evolution is tracked deterministically with  $N \approx 3 6$  macro-bubbles!
- These macro-bubbles are centered at quadrature nodes
- Therefore all unclosed terms appearing in equations for moments are closed with great accuracy
- Two distributions share same moments of NDF:

$$M_{k,l}(\mathbf{x},t) = \iint n(L,\phi_b;\mathbf{x},t)L^k\phi_b^l \,\mathrm{d}L \,\mathrm{d}\phi_b$$

• Sharing same moments does not imply that quadrature has to be realizable (for example  $M_{2,1}$  has to be included!)



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### Quadrature Realizability



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Simulation of Stirred Tanks with QBMM





Without including  $M_{2,1}$  quadrature is not realizable!

æ



### Let us now consider a realistic stirred tank

- Rushton turbine (six blades) reactor volume 15,3 I
- Gassing rate  $\approx$  0,062 l/s; stirring rate 100–300 rpm
- Flow field simulation ANSYS/Fluent13 DSMC in-house code



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Breakage

Flows with Coalescence and

**OBMM** for Bubble

Simulation of Stirred

Tanks with OBMM

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## **DSMC** for Stirred Tanks

### Effect number of comp. on gas hold-up and Sauter diameter



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## **DSMC** for Stirred Tanks

### Bubble size-composition in two regions



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### Effect of chemical reaction (Ha = $\sqrt{kC_{O_2}D}/k_l$ )



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### Simulation of Stirred Tanks with QBMM

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### Drag Laws

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Simulation of Stirred Tanks with QBMM +  $\mathbf{C}_{\mathsf{D}}$  Tomiyama with Bakker's correction for accounting for turbulence effects

$$C_{D} = \max\left\{\min\left(\frac{24}{\mathsf{R}_{\bullet}}(1+0.15\mathsf{R}_{\bullet}^{0.687}), \frac{72}{\mathsf{R}_{\bullet}}\right), \frac{8}{3}, \frac{E_{\circ}}{E_{\circ}+4}\right\} \text{ Calculated with } \begin{array}{c} \mu_{err} = \mu_{r} + C_{r}\rho_{r}\varepsilon^{1/3}\sigma^{4/3} \\ \downarrow \\ \mathbf{Bakker's \ correction}} \end{array}\right\}$$

• C<sub>D</sub> calculated by assuming a Terminal Velocity constant and equal to 13 cm/s

$$C_D = \frac{4_{\sigma_s} (\rho_s - \rho_s)}{3\rho_s U_{\infty}^2}$$

#### **Relevant groups**

**Gas Flow Number** 

# $F_{I_g} = \frac{Q_g}{ND^3}$

F

$$F_r = \frac{N^2 D}{g}$$

D: impeller size

- N: stirring rate (rps)
- g: gravity acceleration

0.2



### Drag Laws

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### Drag force is evaluated from terminal velocity taking into account effect of turbulence and swarms ( $U_t = 13 - 8 \text{ cm/s}$ )





## Fluid-Dynamic Regimes in Stirred Tanks

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LUID-DYNAMIC REGIMES
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300rpm 500rpm

Fig_CD= (13*Fr^2)*(D/T)^5 Complete dispersion (Nienow 1977) soglia max per Fig_per avere ricircolo gas	0.0035	0.0273
Fig_CD = 0.2*((D/T)^0.5)*Fr soglia per complete dispersion transition (correlazione 2)	0.0278	0.0773
Fig_F = 30Fr*(D/T)^3.5 sogila min per Fig per avera flooding	0.1705	0.4737



**Complete dispersion** 



Loading



Image: A match the second s

Flooding

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## Fluid-Dynamic Regimes in Stirred Tanks

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### WeP: Cd Terminal Velocity 300rpm





## Fluid-Dynamic Regimes for Impeller

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Simulation of Stirred Tanks with QBMM

	300rpm	500rpm	
Frg_S33 = 3.8*10^-3*((Ra^2/Fr)^0.07)*((D/T)^-0.5) sogila max per avere VC structure (vortax clinging avvitas) VC per 0 <frg<frg_s33< td=""><td>0.0319</td><td>0.0319</td><td></td></frg<frg_s33<>	0.0319	0.0319	
F19_L33 809118 max per avers S33 structure (3 1arge+3cinging cavities) S33 per F19_S33 < F19< F19_L33	0.1000	0.1000	
Fig_LC = 0.025*(D/T)^(-0.5) soglia min per Fig per avere large cavities	0.0426	0.0426	
Fig_L33= Fig_Fiooding=30F;*(D/T)^3.5 sogila max per avere L33 structure (3 smailer+3 larger cavities) L33 per Fig_L33 < Fig< Fig_rooding	0.1705	0.4737	65

After flooding Ragged Cavities (RC)

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vortex cavity



In the second second second second second

clinging cavity

large cavity





## Fluid-Dynamic Regimes for Impeller

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## Power-Number Reduction (RPD)

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### Power-number reduction (RPD) due to presence of liquid



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Laakkonen M, Alopaeus V, Aittamaa J. Validation of bubble breakage, coalescence and mass transfer models for gas-liquid dispersion in agitated vessel. Chemical Engineering Science. 2006, 61: 218-228.

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Ring sparger (12 holes 2 mm of diameter)

Computational domain on half reactor → N<sub>cells</sub>: 226776

Standard Rushton turbine Baffles and blades width: 1.03 cm Shaft diameter: 3.3 cm Disk diameter: 13.6 cm Turbine diameter: 21cm Disk width: 1.06 cm Sparger position: z = -10.5 cm; d = 3.3 cm Sparger width d = 15 mm



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### Different gassing and stirring rates were investigated



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Simulation of Stirred Tanks with QBMM CQMOM: 10 additional scalars are now transported: 9 moments and 1 oxygen concentration inside liquid phase

9 moments of distribution are inverted in order to find weights and nodes of quadrature

 $M_{0,0}, M_{1,0}, M_{2,0}, M_{3,0}, M_{4,0}, M_{5,0}, M_{0,1}, M_{1,1}, M_{2,1} \rightarrow w_1, w_2, w_3, L_1, L_2, L_3, \phi_1, \phi_2, \phi_3$ 

- 2 Source terms of moments due to coalescence, breakage and mass trasfer are calculated
- 3 Source term of the chemical species in liquid is calculated
- O To speed up calculation moment equations are solved at each time step whereas flow field is updated (for 2 sec) every 6 sec



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## **QBMM** for Stirred Tanks

### Results and comparison with experimental data





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## **QBMM** for Stirred Tanks

### Results and comparison with experimental data



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Computational

Models for

Columns

Breakage

## **QBMM** for Stirred Tanks

### Results and comparison with experimental data for configuration 1





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Simulation of Stirred Tanks with QBMM Experimental and simulated mean bubble size (mm) in five different points of the stirred tank for configuration 1

SR, RPM	GR, vvm		R2	R4	R8	R9	R12
155	0.018	Exp.	2.37	2.48	2.29	1.65	3.31
		Sim.	3.10	2.56	2.57	2.63	3.09
220	0.041	Exp.	2.56	3.34	2.57	1.76	3.81
		Sim.	2.66	3.04	2.47	2.50	3.20
220	0.052	Exp.	2.74	2.93	2.17	2.01	3.18
		Sim.	2.45	3.31	2.55	2.65	3.57
250	0.093	Exp.	2.96	3.25	2.43	2.23	3.33
		Sim.	2.56	3.27	2.59	3.05	3.35

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### Global gas hold-up for 390 rpm for configuration 2 Drag coefficient with terminal velocity ( $U_t$ =13-8 cm/s)



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## **QBMM** for Stirred Tanks

# Specific surface area of bubbles $(m^{-1})$ at 250 rpm and 0.052 vvm (left) and at 155 rpm and 0.018 vvm (right)



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## **QBMM** for Stirred Tanks

### Mass transfer coefficient $k_l$ (m s<sup>-1</sup>) at 250 rpm and 0.052 vvm (left) and at 155 rpm and 0.018 vvm (right)





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### Time evolution of oxygen concentration in liquid



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# Example of poor performance of fixed-constant bubble 3-D simulation for mass transfer!



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Application to Bubbly Flows

QBMM for Bubble Columns

Flows with Coalescence and Breakage

Simulation of Stirred Tanks with QBMM

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### Part 6

Computational Models for Polydisperse Particulate and Multiphase Systems

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Application to Clustered-Induced Turbulence

Extension to Dense Flows

Solution Algorithm for All Flow Regimes

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## **APPLICATION TO GAS-PARTICLE FLOWS**

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### **Gas**–Particle Flows

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### Principal characteristics

- gas phase
- particle phase
- finite particle inertia
- collisions
- variable mass loading
- size distribution
- multiphase turbulence

*St<sub>p</sub>* is not negligible, must account for velocity fluctuations



Bidisperse gas-particle flow (PR-DNS of S Subramaniam)

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## Modeling Challenges in Gas-Particle Flows

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### Strong coupling between gas and particle phases

- Wide range of particle volume fractions (even in same flow!)
- Inertial particles with wide range of Stokes numbers
- Collision-dominated to collision-less regimes in same flow
- Granular temperature can be small and large in same flow
- Polydispersity (e.g. size, density, shape) is always present

### Need a modeling framework that can handle all aspects!

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Need a modeling framework that can handle all aspects!



# Mesoscale Kinetic Equation for Particle Phase

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Mesoscale equations are closed to reproduce physics from microscale

• Kinetic equation (KE) for **monodisperse** particles: *n*(*t*, **x**, **v**)

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial x_i} (v_i n) + \frac{\partial}{\partial v_i} [A_i(t, \mathbf{x}, \mathbf{v})n] = \mathbb{C}$$

with closed acceleration  ${\bf A}$  and collision operator  ${\mathbb C}$ 

• Generalized population balance equation (GPBE):  $n(t, \mathbf{x}, \mathbf{v}, \xi)$ 

 $-\frac{\partial n}{\partial t} + \frac{\partial}{\partial x_i} (v_i n) + \frac{\partial}{\partial v_i} [A_i(t, \mathbf{x}, \mathbf{v}, \boldsymbol{\xi})n] + \frac{\partial}{\partial \boldsymbol{\xi}} [G(t, \mathbf{x}, \mathbf{v}, \boldsymbol{\xi})n] = \mathbb{C}$ 

with closed acceleration A, growth G and collision operator  $\mathbb C$ 

#### KE/GPBE is coupled to Navier-Stokes equation for gas phase



# Mesoscale Kinetic Equation for Particle Phase

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#### KE/GPBE is coupled to Navier-Stokes equation for gas phase



# Complexity of Solutions for Gas-Particles Flows

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#### Cluster-induced turbulence

EL simulations: J. S. Capecelatro & O. Desjardins

• average volume fraction:  $\alpha_{p} = 0.01$ 

• 
$$\rho_{\rm p}/\rho_{\rm g} = 1500, \, {\rm Re}_{\rm p} = 1$$

- · elastic collisions
- full 2-way coupling

Eulerian moment model should yield identical results (if closure is accurate)



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# Particle Trajectory Crossing in 2-D

## 10-moment, 9-node CHyQMOM

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# Particle Trajectory Crossing in 3-D

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# 16-moment, 27-node CHyQMOM

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# Do Eulerian and Lagrangian Models Agree?

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# Cluster-induced turbulence

#### Simulation parameters

- Cases 1–6 in Capecelatro et al. JFE (2015)
- volume fraction:  $\alpha_p = 0.01$
- $\rho_p / \rho_g = 1000$ , Re<sub>p</sub> = 0.5
- terminal velocity:  $\mathcal{V} = 0.1 \text{ m/s}$
- cluster length:  $\mathcal{L} = 2.5 \text{ mm}$
- Case 6:  $L_x/\mathcal{L} = 129$ (2048 × 512 × 512)

Euler-Lagrange and Euler-Euler simulations performed on same grid, but not with same numerical schemes



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# Governing Equations for Eulerian Model

10 velocity moments in 3-D

$$\begin{aligned} \frac{\partial \mathbf{M}}{\partial t} + \nabla \cdot \mathbf{F} &= \mathbf{A} + \mathbf{C} \qquad M_{ijk}^{\gamma} = \int v_1^i v_2^j v_3^j f(\mathbf{v}) \, \mathrm{d}\mathbf{v} \\ M_{000}^0 &= \alpha_p \quad \begin{bmatrix} M_{100}^1 \\ M_{010}^1 \\ M_{010}^1 \end{bmatrix} = \alpha_p \mathbf{U}_p \quad \begin{bmatrix} M_{200}^2 & M_{110}^2 & M_{101}^2 \\ M_{100}^2 & M_{020}^2 & M_{011}^2 \\ M_{101}^2 & M_{011}^2 & M_{002}^2 \end{bmatrix} = \alpha_p (\mathbf{U}_p \otimes \mathbf{U}_p + \mathbf{P}_p) \end{aligned}$$

Gauss-Hermite quadrature for free-transport flux F



Computational Models for Polydisperse Particulate and Multiphase Systems

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# Qualitative Comparison of Clustering

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Case 2









Case 4





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## Similar shapes, but EE has slightly longer/wider clusters

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# Quantitative Comparison of One-Point Statistics

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EE has slightly fewer high  $\alpha_p$  values (due to numerics?)

# EE has slightly higher drift velocity (due to larger clusters?)



# Quantitative Comparison of One-Point TKE Statistics

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# EE has lower uncorrelated TKE (due to EL post-processing?)

EE has higher correlated TKE (due to larger clusters?)



Computational Models for Polydisperse

> Multiphase Systems

International

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Professor Application to Gas-Particle

Flows

Flows

Application to

for All Flow Regimes Turbulence

Modeling for Disperse **Multiphase Flows** Cluster-Induced

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Turbulence

# Quantitative Comparison of TKE Anisotropy



EE has slightly higher anisotropy (due to larger clusters?) CIT is highly anisotropic  $\implies$  need full pressure tensor

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Computational Models for

# Quantitative Comparison of Two-Point Statistics



EE has longer clusters (horizontal nearly identical)

EE has larger energetic vortices (due to longer clusters?)

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# Quantitative Comparison of Energy Spectra

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Good agreement at small wavenumbers ( $\kappa d_p < 0.1$ )

EE has less energy than EL at large wavenumbers (due to EL filter for coupling, numerics?)



# Gas-Particle Model for Dilute to Dense Flows

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#### Particle-phase KE

$$\frac{\partial n}{\partial t} + \mathbf{v} \cdot \frac{\partial n}{\partial \mathbf{x}} + \frac{\partial}{\partial \mathbf{v}} \cdot \mathbf{A}n = \mathbb{C}$$

- n(t, x, v): number density function (NDF)
- v: particle velocity
- A: particle acceleration
- C: rate of change of n due to Boltzmann–Enskog collisions and frictional stresses

#### Fluid-phase equations

$$\frac{\partial}{\partial t}\alpha_g\rho_g + \nabla\cdot\alpha_g\rho_g\mathbf{U}_g = 0$$

$$\frac{\partial}{\partial t} \alpha_g \rho_g \mathbf{U}_g + \nabla \cdot \alpha_g \rho_g \mathbf{U}_g \mathbf{U}_g$$
$$= \nabla \cdot \alpha_g \tau_g + \beta_g + \alpha_g \rho_g \mathbf{g}$$

- $\alpha_g = 1 \alpha_p$ : gas volume fraction
- $\beta_g$ : mean particle drag



# Gas-Particle Model for Dilute to Dense Flows

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#### Particle-phase KE

$$\frac{\partial n}{\partial t} + \mathbf{v} \cdot \frac{\partial n}{\partial \mathbf{x}} + \frac{\partial}{\partial \mathbf{v}} \cdot \mathbf{A}n = \mathbb{C}$$

- *n*(*t*, **x**, **v**): number density function (NDF)
- v: particle velocity
- A: particle acceleration
- C: rate of change of n due to Boltzmann–Enskog collisions and frictional stresses

#### Fluid-phase equations

$$\frac{\partial}{\partial t} \boldsymbol{\alpha}_{g} \boldsymbol{\rho}_{g} + \nabla \cdot \boldsymbol{\alpha}_{g} \boldsymbol{\rho}_{g} \mathbf{U}_{g} = 0$$

$$\begin{aligned} \frac{\partial}{\partial t} \boldsymbol{\alpha}_{g} \boldsymbol{\rho}_{g} \mathbf{U}_{g} + \nabla \cdot \boldsymbol{\alpha}_{g} \boldsymbol{\rho}_{g} \mathbf{U}_{g} \mathbf{U}_{g} \\ &= \nabla \cdot \boldsymbol{\alpha}_{g} \boldsymbol{\tau}_{g} + \boldsymbol{\beta}_{g} + \boldsymbol{\alpha}_{g} \boldsymbol{\rho}_{g} \mathbf{g} \end{aligned}$$

- $\alpha_g = 1 \alpha_p$ : gas volume fraction
- $\beta_g$ : mean particle drag



# Governing Equations with Collisional and Frictional Fluxes

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10 velocity moments in 3-D (dilute regime):

$$\begin{aligned} \frac{\partial \mathbf{M}}{\partial t} + \nabla \cdot \mathbf{F} &= \mathbf{S} \qquad M_{ijk}^{\gamma} = \int v_1^i v_2^j v_3^j f(\mathbf{v}) \, \mathrm{d}\mathbf{v} \\ M_{000}^0 &= \alpha_p, \quad \begin{bmatrix} M_{100}^1\\ M_{010}^1\\ M_{001}^1 \end{bmatrix} &= \alpha_p \mathbf{U}_p, \quad \begin{bmatrix} M_{200}^2 & M_{110}^2 & M_{101}^2\\ M_{110}^2 & M_{020}^2 & M_{011}^2\\ M_{101}^2 & M_{011}^2 & M_{002}^2 \end{bmatrix} &= \alpha_p (\mathbf{U}_p \otimes \mathbf{U}_p + \mathbf{P}_p) \end{aligned}$$

Particle-phase equations (dense regime  $\implies 3\Theta_p = trace(\mathbf{P}_p)$ ):

$$\frac{\partial \rho_p \alpha_p}{\partial t} + \nabla \cdot \rho_p \alpha_p \mathbf{U}_p = 0$$

$$\frac{\partial \rho_p \alpha_p \mathbf{U}_p}{\partial t} + \nabla \cdot \rho_p \alpha_p \left( \mathbf{U}_p \otimes \mathbf{U}_p + \mathbf{P}_p + \mathbf{G}_p + \mathbf{Z}_p \right) = \rho_p \alpha_p \mathbf{g} + \rho_p \alpha_p \mathbf{M}_{pg}$$

$$\frac{\partial \rho_p \alpha_p \mathbf{P}_p}{\partial t} + \nabla \cdot \rho_p \alpha_p \left( \mathbf{U}_p \otimes \mathbf{P}_p + \mathbf{Q}_p + \mathbf{H}_p \right) + \rho_p \alpha_p \left[ (\mathbf{P}_p + \mathbf{G}_p) \cdot \nabla \mathbf{U}_p + \left( \nabla \mathbf{U}_p \right)^T \cdot (\mathbf{P}_p + \mathbf{G}_p) \right]$$
$$= \rho_p \alpha_p \mathbf{E}_{pg} + \rho_p \alpha_p \mathbf{C}_p$$



# Kinetic, Collisional and Frictional Fluxes

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Kinetic flux:

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$$\mathbf{U}_{p} \otimes \mathbf{U}_{p} + \mathbf{P}_{p}$$
$$\mathbf{P}_{p} = \Theta_{p}\mathbf{I} - \boldsymbol{\sigma}_{p} = \Theta_{p}\mathbf{I} - 2\boldsymbol{\nu}_{p,k}\mathbf{S}_{p}$$
$$\mathbf{S}_{p} = \frac{1}{2}\left[\nabla\mathbf{U}_{p} + \left(\nabla\mathbf{U}_{p}\right)^{T} - \frac{2}{3}\left(\nabla\cdot\mathbf{U}_{p}\right)\mathbf{I}\right]$$

Collisional flux (pressure infinite for finite  $\alpha_p \approx 0.63$ ):

$$\mathbf{G}_p = \frac{p_{p,c}}{\rho_p \alpha_p} \mathbf{I} - 2 \nu_{p,c} \mathbf{S}_p$$

Frictional flux (pressure infinite for finite  $\alpha_p \approx 0.63$ , null when  $\alpha_p < 0.55$ ):

$$\mathbf{Z}_p = \frac{p_{p,f}}{\rho_p \alpha_p} \mathbf{I} - 2 \nu_{p,f} \mathbf{S}_p$$

Energy fluxes: 
$$\mathbf{U}_p \otimes \mathbf{P}_p + \mathbf{Q}_p + \mathbf{H}_p = \mathbf{U}_p \otimes \mathbf{P}_p - \frac{2}{3} k_{\Theta} \nabla \otimes \mathbf{P}_p$$

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# Kinetic Flux-Splitting Scheme for All Flow Regimes

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$$\frac{\partial \mathbf{M}}{\partial t} + \nabla \cdot \mathbf{h}_1 \mathbf{F} + \nabla \cdot (\mathbf{h}_2 \mathbf{F} + \mathbf{G} + \mathbf{Z}) = \mathbf{S}$$

 $h_1 + h_2 = 1$ 

$$h_2 = \left(\frac{p_{p,c} + p_{p,f}}{p_{p,k} + p_{p,c} + p_{p,f} + \varepsilon}\right)^{\mathsf{F}}$$

 $\frac{\partial \mathbf{M}}{\partial t} + \nabla \cdot h_1 \mathbf{F} = \mathbf{0}$ 

Step 2: Hydrodynamic solver

 $\frac{\partial \mathbf{M}}{\partial t} + \nabla \cdot (\mathbf{h}_2 \mathbf{F} + \mathbf{G} + \mathbf{Z}) = \mathbf{S}$ 







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### 1 Initialize all variables M, $\{\alpha_p, \mathbf{U}_p, \Theta_p, \sigma_p\}$ , and $\{\alpha_g, \mathbf{U}_g, p_g\}$

2 Calculate  $h_1$  and  $h_2$ 

**3 Explicit** Free-transport solver:

Compute kinetic-based moment fluxes to transport the moments Update  $\{\alpha_p, \mathbf{U}_p, \Theta_p, \sigma_p\}$  using moments **M** 

Iterative Hydrodynamic solver:

Solve  $\{\alpha_p, \mathbf{U}_p, \Theta_p\}$  hydrodynamic transport equations Solve gas-phase velocity and pressure,  $\{\mathbf{U}_x, p_x\}$ , equations

- 5 Solve  $\sigma_p$  transport equation
- Update moment set **M** using  $\{\alpha_p, \mathbf{U}_p, \Theta_p, \boldsymbol{\sigma}_p\}$
- Advance in time by repeating from Step 2 until simulation is complete

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### 1 Initialize all variables M, $\{\alpha_p, \mathbf{U}_p, \Theta_p, \sigma_p\}$ , and $\{\alpha_g, \mathbf{U}_g, p_g\}$

#### **2** Calculate $h_1$ and $h_2$

**Explicit** Free-transport solver:

Compute kinetic-based moment fluxes to transport the moments Update  $\{\alpha_p, \mathbf{U}_p, \Theta_p, \sigma_p\}$  using moments **M** 

Iterative Hydrodynamic solver:

Solve  $\{\alpha_p, \mathbf{U}_p, \Theta_p\}$  hydrodynamic transport equations Solve gas-phase velocity and pressure,  $\{\mathbf{U}_g, p_g\}$ , equations

**5** Solve  $\sigma_p$  transport equation

- Update moment set M using  $\{\alpha_p, \mathbf{U}_p, \mathbf{\Theta}_p, \boldsymbol{\sigma}_p\}$
- 7 Advance in time by repeating from Step 2 until simulation is complete

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Turbulence Modeling for Disperse Multiphase Flows Cluster-Induced Turbulence Mesoscale Simulation of CIT Turbulence Model for CIT Concluding Remarks 1 Initialize all variables M,  $\{\alpha_p, \mathbf{U}_p, \Theta_p, \sigma_p\}$ , and  $\{\alpha_g, \mathbf{U}_g, p_g\}$ 

**2** Calculate  $h_1$  and  $h_2$ 

**3 Explicit** Free-transport solver:

Compute kinetic-based moment fluxes to transport the moments Update  $\{\alpha_p, \mathbf{U}_p, \Theta_p, \sigma_p\}$  using moments **M** 

Iterative Hydrodynamic solver

Solve  $\{\alpha_p, \mathbf{U}_p, \Theta_p\}$  hydrodynamic transport equations Solve gas-phase velocity and pressure,  $\{\mathbf{U}_g, p_g\}$ , equations

5 Solve  $\sigma_p$  transport equation

- Update moment set **M** using  $\{\alpha_p, \mathbf{U}_p, \Theta_p, \boldsymbol{\sigma}_p\}$
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# 2-D Bubbling Fluidized Bed

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#### 3-D Wall-Bounded Vertical Channel Instantaneous Fields



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- For dilute flows, simulations use velocity NDF reconstruction and kinetic-based finite-volume methods
- For dense flows, use KBFVM for kinetic flux and "two-fluid" hydrodynamic solver for collisional/frictional fluxes
- Joint mass-velocity NDF allows for polydisperse particles is used for applications involving particle "size" changes



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### Start with homogeneous, laminar flow:

- particles fall under gravity g with  $\rho_p \gg \rho_f$
- Stokes drag time  $\tau_p = \frac{\rho_p}{2} \frac{d_p^2}{18v}$
- particle collisions  $\langle \alpha_n \rangle \approx 0.01$



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- particle collisions  $\langle \alpha_p \rangle \approx 0.01$
- mass loading  $\varphi = rac{
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- integral scales
- dissipation scales
- energy spectra for  $\alpha_p$ ,  $\mathbf{u}_p$ ,  $\mathbf{u}_f$ , ...

#### 2 How do these characteristics depend on flow parameters?

- fluid-phase Reynolds number  $Re_f = \frac{1}{18} \frac{\rho_p}{\alpha} Re_p^2 = \frac{1}{2} St_p Re_p$
- $\circ$  mass loading arphi
- mean volume fraction  $\langle \alpha_p \rangle$
- How is turbulent kinetic energy (TKE) produced and transferred between phases?
  - What are roles of correlated vs. uncorrelated components of TKE?
- **B** How do we derive a one-point turbulence model for CIT?

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- fluid-phase Reynolds number  $Re_f = \frac{1}{18} \frac{\rho_p}{\rho_f} Re_p^2 = \frac{1}{2} St_p Re_p$ 
  - mass loading  $\varphi$
- mean volume fraction  $\langle \alpha_p \rangle$
- How is turbulent kinetic energy (TKE) produced and transferred between phases?
- What are roles of correlated vs. uncorrelated components of TKE?
- **B** How do we derive a one-point turbulence model for CIT?



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Application to Clustered-Induced Turbulence

Extension to Dense Flows

Solution Algorithm for All Flow Regimes

Turbulence Modeling for Disperse Multiphase Flows

Cluster-Induced Turbulence

Mesoscale Simulation of CIT Turbulence Model for CIT Concluding Remarks

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- dissipation scales
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## From Microscale to Mesoscale to Macroscale

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Turbulence Model for CIT Concluding Remarks

### microscale DNS



- Resolve flow around particles
- Particle collisions resolved
- Fluid stresses on particles

#### mesoscale simulation



- Drag model
- Particle collisions resolved
- Clusters are resolved

#### macroscale simulation



- Turbulence model
- Phase-average variables

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 Effect of clusters is modeled



# Mesoscale Computations

(Capecelatro & Desjardins 2013)

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Simulation of CIT Turbulence Model for CIT Concluding Remarks Fluid phase

- NGA arbitrarily high-order DNS/LES code
- Massively parallel
- Conservation of mass, momentum, and kinetic energy

#### Particle phase

- Lagrangian particle tracking
- Newton's 2nd law with Runge-Kutta ODE solver
- Soft-sphere collision model

#### Interphase exchange terms

- Transfer particle volume and momentum to fluid
- Fully conservative and consistent filtering approach
- Transferred data converges under mesh refinement





### Mesoscale Transport Equations

(Capecelatro & Desjardins 2013)

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Concluding Remarks

#### Gas phase

$$\frac{\partial \rho_f(1-\hat{\alpha})}{\partial t} + \nabla \cdot \rho_f(1-\hat{\alpha}) \mathbf{u}_f = 0$$

$$\frac{\partial \rho_f (1 - \hat{\alpha}) \mathbf{u}_f}{\partial t} + \nabla \cdot \rho_f (1 - \hat{\alpha}) \mathbf{u}_f \mathbf{u}_f = -\nabla p_f + \nabla \cdot \boldsymbol{\sigma}_f - \rho_p \hat{\alpha} \hat{\mathcal{A}} + \rho_f (1 - \hat{\alpha}) \mathbf{g}$$
Particles  $(1 \le p \le N_p)$ 

$$\frac{\mathrm{d}\mathbf{x}_p}{\mathrm{d}t} = \mathbf{v}_p \quad \frac{\mathrm{d}\mathbf{v}_p}{\mathrm{d}t} = \mathcal{A}_p + \mathbf{F}_p^{\mathsf{col}} + \mathbf{g}$$

Two-way coupling

$$\hat{\alpha}(t,\mathbf{x}) \approx \sum_{p=1}^{N_p} G(|\mathbf{x} - \mathbf{x}_p(t)|) V_p \quad \hat{\alpha} \hat{\mathcal{A}}(t,\mathbf{x}) \approx \sum_{p=1}^{N_p} \mathcal{A}_p G(|\mathbf{x} - \mathbf{x}_p(t)|) V_p$$

G(x) is an isotropic Gaussian filter with width  $\delta_f = 8d_p$ 

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## Simulation Parameters for CIT

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**Concluding Remarks** 

$d_p$	Particle diameter	0.09			mm
$\dot{\rho_p}$	Particle density	1000			kg/m <sup>3</sup>
$\rho_{f}$	Fluid density	1			kg/m <sup>3</sup>
$v_f$	Fluid kinematic viscosity	1.8×10 <sup>-5</sup>			m²/s
е	Coefficient of restitution	0.9			
$N_p$	Number of particles	55×10 <sup>6</sup>			
g	Gravity magnitude	2.0002	4.0004	8.0008	$m/s^2$
V	Cluster velocity	0.05	0.1	0.2	m/s
£	Cluster length	1.25	2.5	5	mm

#### Non-dimensional parameters

Physical parameters

(			
$\varphi$ Mean mass load	ing 10.1		
<i>Re<sub>p</sub></i> Particle Reynold	s number 0.25	0.5	1
<i>Re<sub>f</sub></i> Fluid Reynolds r	umber 3.5	14	56
$L_x/\mathcal{L}$ Domain length	256	128	64

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### Time Evolution of Cluster Formation

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- Clusters form due to fluid instability
- Positive feedback due to cluster-fluid-velocity correlation
- Steady state reached when fluid turbulence breaks up clusters
- Fluid velocity seen by particles is negatively correlated with α<sub>p</sub>

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• Box size must allow fluid turbulence to fully develop at large scales!



# Particle Volume Fraction and Fluid Velocity vs. Rep



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## Spatially Correlated and Uncorrelated Velocity



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### • $\kappa_p^* = \frac{1}{2} \mathbf{v}_p \cdot \mathbf{v}_p = k_p^* + \frac{3}{2} \Theta_p^*$ is particle property (independent of filter)

- Partition between  $k_p^*$  and  $\Theta_p^*$  depends on filter!
- Use variable filter width  $\delta_f(\alpha_p) = \left(\frac{N_p d_p^3}{\alpha_p}\right)^{1/3}$  with  $N_p = 10$
- Validate by comparing Lagrangian and Eulerian two-point statistics:





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- $\kappa_p^* = \frac{1}{2} \mathbf{v}_p \cdot \mathbf{v}_p = k_p^* + \frac{3}{2} \Theta_p^*$  is particle property (independent of filter)
- Partition between k<sup>\*</sup><sub>p</sub> and Θ<sup>\*</sup><sub>p</sub> depends on filter!
- Use variable filter width  $\delta_f(\alpha_p) = \left(\frac{N_p d_p^3}{\alpha_p}\right)^{1/3}$  with  $N_p = 10$
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### Filter Error for Energy Components

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Turbulence Modeling for Disperse Multiphase Flows Cluster-Induced Turbulence Mesoscale Simulation of CIT Turbulence Model for CIT Concluding Remarks Variable filter width yields good decomposition of  $\kappa_p^*$  to find  $k_p^*$  and  $\Theta_p^*$ 



 $N_p \approx 10$  agrees with Lagrangian 2-pt statistics We use adaptive filter to study instantaneous local fields of  $\mathbf{u}_p$  and  $\delta \mathbf{v}_p$ 



### Dynamics of Granular Temperature Field

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**Concluding Remarks** 

#### Maximum $\Theta^*$ in front of clusters





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### Compressive "Heating" of Particle Phase

 $3\Theta/(2\kappa_n)$ 

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- Maximum compression

   (-∇ ⋅ u<sub>p</sub>) at same location at maximum Θ<sup>\*</sup><sub>p</sub>
- Cluster fall velocity reduced by granular pressure

$$p = \alpha_p \Theta_p^*$$



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### Eulerian Mesoscale Model for Particle Phase

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Concluding Remarks

Kinetic equation for particle number density function (NDF):  $f(t, \mathbf{x}, \mathbf{v}_p)$ 

accumulation	+free transport	=acceleration	+collisions
$\frac{\partial f}{\partial t}$	$+\mathbf{v}_p\cdot \frac{\partial f}{\partial \mathbf{x}}$	$= -\frac{\partial}{\partial \mathbf{v}_p} \cdot \left[ (\mathcal{A}_p + \mathbf{g}) f \right]$	+C[f,f]

where fluid coupling is modeled as (drag dominant when  $\rho_p \gg \rho_f$ )

$$\mathcal{A}_p(t, \mathbf{x}, \mathbf{v}_p) = \frac{1}{\tau_p} (\mathbf{u}_f - \mathbf{v}_p) - \frac{1}{\rho_p} \nabla p_f + \frac{1}{\rho_p} \nabla \cdot \boldsymbol{\sigma}_f$$

Define particle-phase mass, momentum and pressure tensor  $(trace(\mathbf{P}) = 3\Theta_p)$ :

$$\boldsymbol{\alpha}_p = \int f \, \mathrm{d} \mathbf{v}_p \quad \boldsymbol{\alpha}_p \mathbf{u}_p = \int \mathbf{v}_p f \, \mathrm{d} \mathbf{v}_p \quad \boldsymbol{\alpha}_p \mathbf{P} = \int \mathbf{v}_p^{\prime\prime} \otimes \mathbf{v}_p^{\prime\prime} f \, \mathrm{d} \mathbf{v}_p$$

closure with these variables yields anisotropic Gaussian (AG) model

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### Eulerian Mesoscale Model for Particle Phase

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### **Eulerian Transport Equations**

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#### Gas phase

$$\frac{\partial \rho_f \alpha_f}{\partial t} + \nabla \cdot \rho_f \alpha_f \mathbf{u}_f = 0$$

$$\frac{\partial \rho_f \alpha_f \mathbf{u}_f}{\partial t} + \nabla \cdot \rho_f \alpha_f \mathbf{u}_f \otimes \mathbf{u}_f = -\nabla p_f + \nabla \cdot \boldsymbol{\sigma}_f - \rho_p \alpha_p \mathcal{A}_p + \rho_f \alpha_f \mathbf{g}$$

#### Particle phase

$$\frac{\partial \rho_p \alpha_p}{\partial t} + \nabla \cdot \rho_p \alpha_p \mathbf{u}_p = 0$$

$$\frac{\partial \rho_p \alpha_p \mathbf{u}_p}{\partial t} + \nabla \cdot \rho_p \alpha_p (\mathbf{u}_p \otimes \mathbf{u}_p + \mathbf{P}) = \rho_p \alpha_p (\mathcal{A}_p + \mathbf{g})$$

$$\frac{\partial \rho_p \alpha_p \mathbf{P}}{\partial t} + \nabla \cdot \rho_p \alpha_p (\mathbf{u}_p \otimes \mathbf{P} + \mathbf{Q}) = -\rho_p \alpha_p (\mathbf{P} \cdot \nabla \mathbf{u}_p)^{\dagger} - \rho_p \alpha_p \frac{2}{\tau_p} \mathbf{P} + \rho_p \alpha_p \frac{2}{\tau_c} (\Delta^* - \mathbf{P})$$

coupling term  $\mathcal{R}_p$  is closed, but energy flux **Q** requires kinetic theory closure



# Particle Volume Fraction EL vs. EE-AG for $Re_p = 0.5$

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### Comparison Between EL and EE-AG

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1.4 1.2 1.0  $2k_p/\langle U_{p,x}\rangle_p^2$ 0.8 0.6 0.4 0.2 0.0 100

 $L_x/\mathcal{L}$ 



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### Particle Volume Fraction Distribution

EE-AG

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### Energy Spectra

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Turbulence Model for CIT Concluding Remarks • Euler-Lagrange simulation

- Collisions are treated exactly (i.e. no kinetic theory model)
- Coupling to fluid uses spatial filter ( $\delta_f pprox d_p$ )
- Provides most accurate approximation of flow physics

#### • Euler-Euler simulation

- Collisions are not treated exactly (anisotropic BGK closure)
- · Coupling to fluid is exact
- Agreement with EL simulation is satisfactory for collisional flow

#### • Turbulence model for homogeneous CIT

- Rigorous derivation starting from Eulerian transport equations
- Unclosed terms can be found from EL or EE simulations
- Multiphase Reynolds-stress model (RSM)



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Application to Gas–Particle Flows

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Concluding Remarks

#### • Euler-Lagrange simulation

- Collisions are treated exactly (i.e. no kinetic theory model)
- Coupling to fluid uses spatial filter  $(\delta_f \approx d_p)$
- Provides most accurate approximation of flow physics

#### • Euler-Euler simulation

- Collisions are not treated exactly (anisotropic BGK closure)
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#### Turbulence model for homogeneous CIT

- Rigorous derivation starting from Eulerian transport equations
- Unclosed terms can be found from EL or EE simulations
- Multiphase Reynolds-stress model (RSM)



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## Glossary of Terms for CIT

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Due to spatial homogeneity, the turbulence model has production, exchange, dissipation and reorientation terms

Key	Physical meaning
CD	Dissipation/reorientation of P due to collisions
DE	Exchange of momentum/Reynolds stresses/P due to fluid drag
DP	Production of $\langle u_{f1}^{\prime\prime\prime2} \rangle_f$ by fluid drag due to clusters
PE	Exchange of momentum/Reynolds stresses due to fluid pressure
PS	Pressure-strain reorientation of Reynolds stresses
VD	Viscous dissination of Reynolds stresses

VE Exchange of momentum/Reynolds stresses due to viscous stresses

Note: CIT is nearly 1-D turbulence with  $\langle u_{f,1}^{\prime\prime\prime\prime2} \rangle_f \gg \langle u_{f,2}^{\prime\prime\prime\prime2} \rangle_f = \langle u_{f,3}^{\prime\prime\prime\prime2} \rangle_f$ 

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# Reynolds-Averaged Equations for CIT I

Statistically Homogeneous

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**Concluding Remarks** 

• Particle phase: phase average  $\langle \cdot \rangle_p = \langle \alpha_p \cdot \rangle / \langle \alpha_p \rangle$ 

$$\frac{\mathrm{d}\langle u_{p,1}\rangle_p}{\mathrm{d}t} = \frac{1}{\tau_p} \left( \langle u_{f,1}\rangle_p - \langle u_{p,1}\rangle_p \right) \qquad \mathsf{DE}$$
$$+ \frac{1}{\rho_p} \left( \left( \frac{\partial \sigma_{f,1i}}{\partial x_i} \right)_p - \left( \frac{\partial p_f}{\partial x_1} \right)_p \right) \qquad \mathsf{VE/PE}$$
$$+ g$$

$Re_p$	$\frac{\langle u_{p,1} \rangle_p}{V}$	$\frac{\langle u_{f,1} \rangle_p}{V}$	DE	PE	VE	g
0.25	-3.009	-1.891	2.236	0.007	$10^{-7}$	-2
0.5	-2.476	-1.420	4.224	0.013	$10^{-7}$	-4
1.0	-2.278	-1.246	8.255	0.029	$10^{-7}$	-8



# **Reynolds-Averaged Equations for CIT II**

Statistically Homogeneous

2

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**Concluding Remarks** 

$$\frac{1}{2} \frac{\mathrm{d}\langle u_{p,1}^{\prime\prime} \rangle_{p}}{\mathrm{d}t} = \frac{1}{\tau_{p}} \left( \langle u_{f,1}^{\prime\prime\prime} u_{p,1}^{\prime\prime} \rangle_{p} - \langle u_{p,1}^{\prime\prime2} \rangle_{p} \right) \qquad \mathsf{DE}$$

$$+ \left\langle \Theta_{p} \frac{\partial u_{p,1}^{\prime\prime}}{\partial x_{1}} \right\rangle_{p} - \left\langle \sigma_{p,1i} \frac{\partial u_{p,1}^{\prime\prime}}{\partial x_{i}} \right\rangle_{p} \qquad \mathsf{PS/VD}$$

$$+ \frac{1}{\tau_{p}} \left( \left\langle u_{p,1}^{\prime\prime} \frac{\partial \sigma_{f,1i}^{\prime}}{\partial x_{1}} \right\rangle_{p} - \left\langle u_{p,1}^{\prime\prime2} \frac{\partial u_{p,1}^{\prime\prime}}{\partial x_{i}} \right\rangle_{p} \qquad \mathsf{PS/VD}$$

$$+ \frac{1}{\rho_p} \left( \left\langle u_{p,1}^{\prime\prime} \frac{\partial \sigma_{f,1i}}{\partial x_i} \right\rangle_p - \left\langle u_{p,1}^{\prime\prime} \frac{\partial \rho_f}{\partial x_1} \right\rangle_p \right) \qquad \qquad \mathsf{VE/PE}$$

$Re_p$	$\frac{\langle u_{p,1}^{\prime\prime 2}\rangle_p}{2k_p}$	PS	VD	DE	PE	VE
0.25	0.809	-0.022	-0.043	0.103	-0.001	$10^{-9}$
0.5	0.788	-0.075	-0.141	0.274	-0.001	$10^{-9}$
1.0	0.814	-0.275	-0.539	0.879	-0.005	$10^{-9}$



# Reynolds-Averaged Equations for CIT III

Statistically Homogeneous

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**Concluding Remarks** 

$$\frac{1}{2} \frac{\mathrm{d}\langle u_{p,2}^{\prime\prime\prime} \rangle_{p}}{\mathrm{d}t} = \frac{1}{\tau_{p}} \left( \langle u_{f,2}^{\prime\prime\prime} u_{p,2}^{\prime\prime} \rangle_{p} - \langle u_{p,2}^{\prime\prime2} \rangle_{p} \right) \qquad \mathsf{DE}$$

$$+ \left\langle \Theta_{p} \frac{\partial u_{p,2}}{\partial x_{2}} \right\rangle_{p} - \left\langle \sigma_{p,2i} \frac{\partial u_{p,2}}{\partial x_{i}} \right\rangle_{p} \qquad \mathsf{PS/VD}$$

$$= 1 \left( \left\langle u_{p} \right\rangle \frac{\partial \sigma_{f,2i}'}{\partial x_{i}} \right\rangle \left\langle u_{p} \right\rangle \frac{\partial p_{f}'}{\partial x_{i}} \right) \qquad \mathsf{NS/VD}$$

$$+ \frac{1}{\rho_p} \left( \left\langle u_{p,2}'' \frac{\partial \sigma_{f,2i}}{\partial x_i} \right\rangle_p - \left\langle u_{p,2}'' \frac{\partial \rho_f}{\partial x_2} \right\rangle_p \right) \qquad \text{VE/PE}$$

$Re_p$	$\frac{\langle u_{p,2}^{\prime\prime 2}\rangle_p}{2k_p}$	PS	VD	DE	PE	VE
0.25	0.096	0.008	-0.013	0.008	$10^{-4}$	$-10^{-5}$
0.5	0.106	0.027	-0.044	0.021	$10^{-4}$	$-10^{-5}$
1.0	0.093	0.093	-0.154	0.062	$10^{-3}$	$-10^{-4}$



#### Reynolds-Averaged Equations for CIT IV Statistically Homogeneous

 $\overline{2}$ 

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**Concluding Remarks** 

$$\frac{1}{2} \frac{d\langle P_{11} \rangle_p}{dt} = -\frac{1}{\tau_p} \langle P_{11} \rangle_p \qquad \text{DE}$$
$$-\left\langle \Theta_p \frac{\partial u_{p,1}''}{\partial x_1} \right\rangle_p + \left\langle \sigma_{p,1i} \frac{\partial u_{p,1}''}{\partial x_i} \right\rangle_p \qquad \text{PS/VD}$$
$$+ \frac{6}{\sqrt{\pi} d_p} \langle \alpha_p \Theta_p^{1/2} \left( \Delta_{11}^* - P_{11} \right) \rangle_p \qquad \text{CD}$$

$Re_p$	$\frac{\langle P_{11} \rangle_p}{3 \langle \Theta_p \rangle_p}$	PS	VD	DE	CD
0.25	0.621	0.022	0.043	-0.082	-0.030
0.5	0.528	0.075	0.141	-0.192	-0.096
1.0	0.507	0.275	0.539	-0.480	-0.402



# Reynolds-Averaged Equations for CIT V

Statistically Homogeneous

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**Concluding Remarks** 

$$\frac{\mathrm{d}\langle P_{22}\rangle_p}{\mathrm{d}t} = -\frac{1}{\tau_p} \langle P_{22}\rangle_p \qquad \qquad \mathsf{DE}$$
$$-\left\langle \Theta_p \frac{\partial u_{p,2}''}{\partial x_2} \right\rangle_p + \left\langle \sigma_{p,2i} \frac{\partial u_{p,2}''}{\partial x_i} \right\rangle_p \qquad \qquad \mathsf{PS/VD}$$
$$+ \frac{6}{\sqrt{\pi}d_p} \langle \alpha_p \Theta_p^{1/2} \left( \Delta_{22}^* - P_{22} \right) \rangle_p \qquad \qquad \mathsf{CD}$$

$Re_p$	$\frac{\langle P_{22} \rangle_p}{3 \langle \Theta_p \rangle_p}$	PS	VD	DE	CD
0.25	0.198	-0.008	0.013	-0.025	0.011
0.5	0.236	-0.027	0.044	-0.086	0.030
1.0	0.246	-0.093	0.154	-0.233	0.119



# Reynolds-Averaged Equations for CIT VI

Statistically Homogeneous

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**Concluding Remarks** 

• Fluid phase: phase-average velocity  $\langle u_{f,1} \rangle_f = 0$ 

$$\frac{d\langle u_{f,1}^{\prime\prime\prime2}\rangle_{p}}{dt} = \frac{\varphi}{\tau_{p}} \left( \langle u_{f,1}^{\prime\prime\prime\prime}u_{p,1}^{\prime\prime}\rangle_{p} - \langle u_{f,1}^{\prime\prime\prime\prime2}\rangle_{p} \right) + \frac{\varphi}{\tau_{p}} \langle u_{f,1}^{\prime\prime\prime}\rangle_{p} \langle u_{p,1}\rangle_{p} \qquad \text{DE/DP} \\
+ \frac{1}{\rho_{f}} \left( \left\langle p_{f} \frac{\partial u_{f,1}^{\prime\prime\prime\prime}}{\partial x_{1}} \right\rangle - \left\langle \sigma_{f,1i} \frac{\partial u_{f,1}^{\prime\prime\prime\prime}}{\partial x_{i}} \right\rangle \right) \qquad \text{PS/VD} \\
- \frac{\varphi}{\rho_{p}} \left( \left\langle u_{f,1}^{\prime\prime\prime} \frac{\partial \sigma_{f,1i}^{\prime}}{\partial x_{i}} \right\rangle_{p} + \left\langle u_{f,1}^{\prime\prime\prime} \frac{\partial p_{f}^{\prime}}{\partial x_{1}} \right\rangle_{p} \right) \qquad \text{VE/PE}$$

$Re_p$	$\frac{\langle u_{f,1}^{\prime\prime\prime 2}\rangle_p}{2k_f}$	PS	VD	DP	DE	PE	VE
0.25	0.810	-0.465	-0.219	5.747	-5.329	0.012	$-10^{-7}$
0.5	0.801	-1.380	-0.365	14.21	-12.94	0.030	$-10^{-7}$
1.0	0.815	-4.643	-0.719	45.89	-41.47	0.116	$-10^{-7}$



#### Reynolds-Averaged Equations for CIT VII Statistically Homogeneous

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**Concluding Remarks** 

 $\frac{1}{2}\frac{\mathrm{d}\langle u_{f,2}^{\prime\prime\prime2}\rangle_{p}}{\mathrm{d}t} = \frac{\varphi}{\tau_{p}}\left(\langle u_{f,2}^{\prime\prime\prime}u_{p,2}^{\prime\prime}\rangle_{p} - \langle u_{f,2}^{\prime\prime\prime2}\rangle_{p}\right) \qquad \mathsf{DE}$ 

$$+ \frac{1}{\rho_f} \left( \left\langle p_f \frac{\partial u_{f,2}^{\prime\prime\prime}}{\partial x_2} \right\rangle - \left\langle \sigma_{f,2i} \frac{\partial u_{f,2}^{\prime\prime\prime}}{\partial x_i} \right\rangle \right) \qquad \mathsf{PS/VE}$$

$$-\frac{\varphi}{\rho_p}\left(\left(u_{f,2}^{\prime\prime\prime}\frac{\partial\sigma_{f,2i}^{\prime}}{\partial x_i}\right)_p + \left(u_{f,2}^{\prime\prime\prime}\frac{\partial p_f^{\prime}}{\partial x_2}\right)_p\right) \qquad \qquad \mathsf{VE/PE}$$

$Re_p$	$\frac{\langle u_{f,1}^{\prime\prime\prime 2}\rangle_p}{2k_f}$	PS	VD	DE	PE	VE
0.25	0.095	0.237	-0.012	-0.266	-0.003	$10^{-4}$
0.5	0.099	0.705	-0.023	-0.749	-0.010	$10^{-4}$
1.0	0.093	2.384	-0.044	-2.490	-0.037	$10^{-3}$



## Kinetic Energy Balance in Fully Developed CIT

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 $\frac{2k_f}{V^2}$  $\frac{2\kappa_p}{\sqrt{2}}$  $\frac{k_p}{\kappa_n}$  $Re_p$ 0.25 19.52 13.63 0.90 0.5 11.27 7.78 0.88 5.411.0 8.04 0.89

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 $\begin{array}{l} \text{DE}_1 \text{: drag exchange} \approx 22\% \\ \text{DE}_2 \text{: drag dissipation} \approx 78\% \end{array}$ 

In CIT,  $\approx$  90% of particle-phase KE is spatially correlated



### Reynolds-Stress Model for Fully Developed CIT I

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Concluding Remarks

#### • Particle phase:

$$\langle u_{p,1} \rangle_p = \langle u_{f,1}^{\prime\prime\prime} \rangle_p + \mathcal{V}$$

where drift velocity is  $\langle u_{f,1}^{\prime\prime\prime} \rangle_p = C_g \langle u_{p,1} \rangle_p$  with  $C_g$  =0.63, 0.57, 0.55 (vs.  $Re_p$ )

$$0 = \tau_p \mathcal{R}_{p,11} - \tau_p \epsilon_{p,11} + \beta_{fp} \langle u_{p,1}^{\prime\prime 2} \rangle_p^{1/2} \langle u_{f,1}^{\prime\prime\prime 2} \rangle_f^{1/2} - \langle u_{p,1}^{\prime\prime 2} \rangle_p$$

$$0 = \tau_p \mathcal{R}_{p,22} - \tau_p \epsilon_{p,22} + \beta_{fp} \langle u_{p,2}^{\prime\prime 2} \rangle_p^{1/2} \langle u_{f,2}^{\prime\prime\prime 2} \rangle_f^{1/2} - \langle u_{p,2}^{\prime\prime 2} \rangle_p$$

where  $\beta_{fp} = 0.876$  and pressure-redistribution tensor is modeled as

$$\mathcal{R}_{p,ii} = -C_R \frac{\varepsilon_p}{k_p} \left( \langle u_{p,i}^{\prime\prime 2} \rangle_p - \frac{2}{3} k_p \right) \text{ with } C_R = 0.179 \text{ (vs. 1.8)}$$
$$\epsilon_{p,ii} = 2 \left[ f_s \frac{\langle u_{p,i}^{\prime\prime 2} \rangle_p}{2k_p} + (1 - f_s) \frac{1}{3} \right] \varepsilon_p \text{ with } f_s = 0.93$$



### Reynolds-Stress Model for Fully Developed CIT II

$$0 = \tau_p \epsilon_{p,11} - \langle P_{11} \rangle_p + C_c \frac{\tau_p}{\tau_c} \left( \Delta_{11} - \langle P_{11} \rangle_p \right)$$
$$0 = \tau_p \epsilon_{p,22} - \langle P_{22} \rangle_p + C_c \frac{\tau_p}{\tau_c} \left( \Delta_{22} - \langle P_2 \rangle_p \right)$$
$$= 2 \text{ and } \Delta_{ii} = \frac{1}{4} (1 + e)^2 \langle \Theta_p \rangle_p + \frac{1}{4} (1 - e)^2 \langle P_{ii} \rangle_p$$

#### • Fluid phase:

with  $C_c$ 

$$\begin{split} 0 &= \tau_p \mathcal{R}_{f,11} - \tau_p \epsilon_{f,11} + \varphi \beta_{fp} \langle u_{p,1}^{\prime\prime 2} \rangle_p^{1/2} \langle u_{f,1}^{\prime\prime\prime 2} \rangle_f^{1/2} - \varphi \beta_f \langle u_{f,1}^{\prime\prime\prime 2} \rangle_f + \mathcal{DP}_{11} \\ 0 &= \tau_p \mathcal{R}_{f,22} - \tau_p \epsilon_{f,22} + \varphi \beta_{fp} \langle u_{p,2}^{\prime\prime\prime 2} \rangle_p^{1/2} \langle u_{f,2}^{\prime\prime\prime 2} \rangle_f^{1/2} - \varphi \beta_f \langle u_{f,2}^{\prime\prime\prime\prime 2} \rangle_f \end{split}$$

where  $\beta_f = 1.03$  and pressure-redistribution tensor is modeled as

$$\mathcal{R}_{f,ii} = -C_R \frac{\varepsilon_f}{k_f} \left( \langle u_{f,i}^{\prime\prime\prime 2} \rangle_f - \frac{2}{3} k_f \right) - C_{\mathcal{D}} \left( \mathcal{DP}_{ii} - \frac{2}{3} \mathcal{DP} \right) \text{ with } C_{\mathcal{D}} = 0.139 \text{ (vs. 0.6)}$$
  
$$\epsilon_{f,ii} = 2 \left[ f_s \frac{\langle u_{f,i}^{\prime\prime\prime 2} \rangle_f}{2k_f} + (1 - f_s) \frac{1}{3} \right] \varepsilon_f, \ \mathcal{DP}_{11} = \frac{2\varphi}{\tau_p} C_g \langle u_{p,1} \rangle_p^2, \ \mathcal{DP}_{22} = 0, \ \mathcal{DP} = \frac{1}{2} \mathcal{DP}_{11}$$

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**Concluding Remarks** 



### **Dissipation Rate Model**

Form of dissipation model is critical for overall performance!

$$0 = -C_{2,\epsilon}St_f\varepsilon_f + 2C_3\varphi\left(\beta_{fp}\varepsilon_f^{1/2}\varepsilon_p^{1/2} - \beta_f\varepsilon_f\right) + C_4St_p\mathcal{DP}$$
$$0 = -C_{2,\epsilon}St_p\varepsilon_p + 2C_3\left(\beta_{fp}\varepsilon_f^{1/2}\varepsilon_p^{1/2} - \varepsilon_p\right)$$
with  $C_{2,\epsilon} = C_4 = 1.92$  and  $C_3 = 0.736$ 

Stokes numbers are defined by  $St_f = \frac{\tau_p \varepsilon_f}{k_f}$  and  $St_p = \frac{\tau_p \varepsilon_p}{k_p}$ 

#### In fully developed CIT:

$$St_f = 0.25$$
  $St_p = 0.19$   $\frac{k_f}{k_p} \approx 1.6$ 

Compared to sheared turbulence,  $C_R$  and  $C_D$  are significantly smaller

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for CIT

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Turbulence Mesoscale

Simulation of CIT Turbulence Model for CIT

Concluding Remarks

# Concluding Remarks on CIT I

#### **Cluster-Induced Turbulence**

- CIT arises due to mean velocity difference
- Velocity difference arises due to body force or inlet conditions
- With constant velocity difference, CIT is homogeneous and stationary
- TKE is produced by fluid velocity fluctuations seen by the particles
- CIT is anisotropic in direction of mean velocity, but otherwise diagonal



## Concluding Remarks on CIT II

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Cluster-Induced Turbulence

Mesoscale Simulation of CIT Turbulence Model for CIT

Concluding Remarks

#### **Mesoscale Simulation of CIT**

- Lagrangian particle tracking best captures flow physics
- · Wide separation of scales between filter and cluster sizes exists
- Local Eulerian fields can be extracted with  $\alpha_p$ -dependent filter
- Converged statistics require very large domains  $\gg \mathcal{L}!$

#### **Turbulence Model for CIT**

- CIT depends on a relatively small number of correlations
- Drift velocity changes mean drag and produces fluid TKE through  $C_g$
- Reynolds-stress model needed to describe anisotropy
- Principal modeling challenges stem from  $\varepsilon_f$  and  $\varepsilon_p$ , but choices limited

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### Concluding Remarks on CIT III

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Turbulence Model for CIT

Concluding Remarks

#### **Some Open Questions**

- What exactly determines the cluster size distribution?
- Are CIT statistics (one-point, two-point, ...) self similar?
- How do CIT statistics depend on dimensionless parameters (*Re<sub>p</sub>*, φ, ...)?
- How do statistics change when homogeneous mean shear is added?



## Particle-Laden Channel Flow

Effect of mass loading

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Concluding Remarks

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