

# Quadrature-based moment methods for multiphase flows

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## POLITECNICO DI TORINO (ITALY)

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- ▶ Nathan Quadrio and Claudio Canuto (Maths)



## KING ABDULLAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

- ▶ Raul Tempone
- ▶ Häkon Hoel
- ▶ SRI center for Uncertainty Quantification
- ▶ Stochastic Numerics Group



## ICES, THE UNIVERSITY OF TEXAS AT AUSTIN

- ▶ Serge Prudhomme (now at EP Montreal)
- ▶ Ivo Babuska
- ▶ Masha Prodanovic (Petrol. Eng.)



## DIMENSIONLESS NUMBERS

- ▶ **Reynolds** number (fluid or particles)  $Re = \frac{U^{f,r} L}{\nu}$
- ▶ Particles **Stokes** number  $St = \frac{\tau^p}{\tau_f} = \frac{\tau^p U^f}{L}$
- ▶ **Knudsen** number  $Kn = \frac{\lambda}{L}$

**Re  $\gg 1 \rightarrow$  transition to turbulence**  
**small scale and collisions,  $Kn > 10^{-3} \rightarrow$  non-equilibrium effects**  
**poly-dispersity, different St, evolving size  $\rightarrow$  differential segregation**

Problem	Model	Tool
Turbulence Poly-dispersity Collisions Multi-phase	Large Eddy Simulation (LES) Population Balance Eq. (PBE) Boltzmann Eq. Eulerian/Mixture	QBMM <sup>1</sup> QBMM Algebraic Slip
Random heterogeneous materials	DNS + upscaling	

<sup>1</sup>QBMM=Quadrature-Based Moment Method

## FLUID DYNAMICS AND POROUS MEDIA - APPLICATIONS

- ▶ **Pore-scale simulations (single and multi-phase)**
- ▶ Microfluidics, drop impacts on structured surfaces
- ▶ Particulate processes in turbulent flows, colloid deposition
- ▶ Momentum transfer closures for polydispersed flows

## MULTISCALE SIMULATIONS - NUMERICS

- ▶ Numerical studies on convergence properties of flow in complex geometries
- ▶ **Upscaling/model reduction of PDEs in subsurface flows and in Lithium-ion batteries**
- ▶ **Multilevel Monte Carlo sampling for flows with random geometry/parameters**
- ▶ Discretization of PDF equations by quadrature-based moment methods

## UQ AND STOCHASTIC MODELLING

- ▶ **Bayesian inference for calibration and validation of macro-scale models**
- ▶ Dynamic and static data assimilation with mean-field Ensemble Kalman Filter
- ▶ High-dimensional interpolation and surrogates for machine learning in MD
- ▶ **PDF closures for turbulent and porous media flows**



## Kinetic and PDF equations

- Smoluchowski coagulation equation
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- Boltzmann equation (BE)
- Method of Moments
- Generalized population balance equation (GPBE)

## Quadrature-based moment methods

- Numerical Methods and Closure problem
- Gaussian quadrature
- QMOM and DQMOM
- EQMOM
- Multivariate case
- Implementation in CFD codes / spatial inhomogeneity

## Applications

- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
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- ▶ D. Marchisio and R. Fox, Computational Models for Polydisperse Particulate and Multiphase Systems (Cambridge Univ, 2012)
- ▶ Rodney Fox, Computational Models for turbulent reacting flows (Cambridge Univ, 2003)
- ▶ H. Struchtrup, Macroscopic Transport Equations for Rarefied Gas Flows (Springer, 2005)
- ▶ Cercignani, The Boltzmann equation and its applications (Springer, 1988)
- ▶ W. Gautschi, Orthogonal Polynomials (Oxford Sci., 2004)
- ▶ D. Ramkrishna, Population Balances (Academic Press, 2000)
- ▶ my PhD thesis (2012)
- ▶ O. Le Maître and O. Knio, Spectral Methods for Uncertainty Quantification (Springer, 2010)
- ▶ C.W. Gardiner, Handbooks of Stochastic Methods (Springer, 2004)
- ▶ Articles and reviews of R. Fox, D. Marchisio, A. Passalacqua, P. Vedula, L. Massot, ...

Please keep in mind the following notation:

- ▶ Probability Density function (PDF):  $f$  or  $P$
- ▶ Number Density Function (NDF):  $n$
- ▶ Space coordinates  $\mathbf{x}$ , velocity  $U$
- ▶ Subscripts:  $p$  for particles,  $f$  for fluid
- ▶ Statistical moments:  $M$  or  $\mu$
- ▶ Particle mass:  $m$
- ▶ Polynomial of order  $\alpha$ :  $P_\alpha$
- ▶ Internal variables: general  $\xi$  (or  $\xi$ ), size  $L$ , species concentration  $\phi$
- ▶ Quadrature nodes denoted by the internal variable with subscript  $i$
- ▶ Quadrature weights denoted by  $w_i$
- ▶  $\Omega_\xi$  (or simply  $\mathbb{R}$ ): support for variable  $\xi$

NO Einstein summation convention

This is just a modelling and numerical overview. Sorry but there will be no mathematical details (spaces, BCs, probability spaces, proofs, etc...), use your intuition (and ask if needed)!!

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Describe particle aggregation/coagulation

$$\frac{\partial n(L, t)}{\partial t} = \frac{1}{2} \int_0^L K(L-\tilde{L}, \tilde{L}) n(L-\tilde{L}, t) n(\tilde{L}, t) d\tilde{L} - \int_0^\infty K(L, \tilde{L}) n(L, t) n(\tilde{L}, t) d\tilde{L}$$

- ▶ Not to be confused with the Smoluchowski equation (drift-diffusion equation)
- ▶ Integro-differential equation
- ▶ Number density  $n$  of particles with size  $L$
- ▶ No spatial dependence
- ▶ RHS ( $\mathcal{Q}$ ) has a gain and a loss term written in terms of the aggregation frequency  $K$
- ▶  $K$  is usually very complex and non-linear

Very interesting mathematical topic (stability, linearization, large-time asymptotics), see works of Klemens Fellner (Graz)

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Extension of the Smoluchowski coagulation equation, very popular in Chemical Engineering, Biology and Social Models

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial x} \cdot (Un) + \frac{\partial}{\partial \xi} \cdot (Gn) = \mathcal{Q}$$

- ▶  $n = n(\xi; x, t)$  number of particles per unit volume
- ▶  $\xi_i$  generic internal variables (volume, size, area, composition, other properties)
- ▶  $U$  given advection velocity field
- ▶  $\mathcal{Q}$  describe the generic particulate process with Birth (nucleation), Breakage (Fragmentation) and Aggregation (Coagulation)<sup>2</sup>

$$\mathcal{Q} = \mathcal{Q}_0 + \mathcal{Q}_1(n) + \mathcal{Q}_2(n, n)$$

- ▶  $G$  describe growth of particles (velocity in phase space  $\xi$ )
- ▶ Usually written for spatially inhomogeneous systems and coupled with CFD to simulate dispersed bubbles and particles

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<sup>2</sup>with frequency kernels that can be seen as upscaled jump processes

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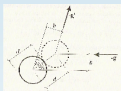
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## Molecular encounters for hard-spheres potential



- ▶  $d$  is the molecular diameter
- ▶  $g = U - U_*$  is the pre-collision velocity difference
- ▶  $g' = U' - U'_*$  is the post-collision velocity difference

Number and momentum are conserved during a collision

$$m + m_* = m' + m'_*; \quad U + U_* = U' + U'_*$$

as well as kinetic energy (in the case of elastic collisions)

$$U \cdot U + U_* \cdot U_* = U' \cdot U' + U'_* \cdot U'_*$$

From the Liouville n-particles equation, assuming **indistinguishable** particle and the "**Stosszahlansatz**" (molecular chaos<sup>3</sup> hypothesis), the Boltzmann equation is obtained

$$\frac{\partial n(U)}{\partial t} + \frac{\partial}{\partial x} \cdot (Un(U)) + \frac{\partial}{\partial U} \cdot (An(U)) = \int_{\mathbb{R}^3} \int_{\mathbb{S}^+} [n(U')n(U'_*) - n(U)n(U_*)] \beta(g, x) \, ds \, dU_*$$

- ▶  $A$  is the acceleration,
- ▶  $\mathbb{S}^+$  is the solid angle
- ▶  $\beta(g, x)$  is the collision kernel

Equations with similar structure: Vlasov (no collisions), Williams-Boltzmann spray equation, ...

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<sup>3</sup>particles are uncorrelated, two-particles PDF is product of one-particle PDF

Most of the studies and methods for BE are based on the concept of **Equilibrium Distribution**

- ▶ The equilibrium distribution  $f_{eq}$  is such that  $\mathcal{Q}(f_{eq}, f_{eq}) = 0$
- ▶ Also called "**Maxwell-Boltzmann**" or "**Maxwellian**" distribution, a Gaussian in the standard case
- ▶ Fixing the first 2 moments (3 in case of NDF), only one Gaussian exist
- ▶ If one wants to study non-equilibrium phenomena, more moments must be studied
- ▶ **Grad's moment method** is based on small deviations from equilibrium

$$f \approx f_{eq}(1 + a_1 H_1(v) + a_2 H_2(v) + \dots)$$

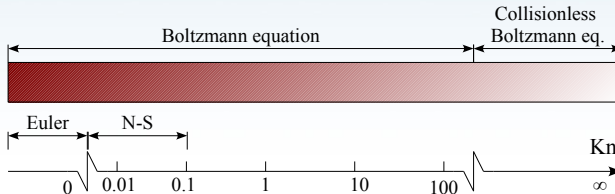
- ▶ Other methods (such as Lattice Boltzmann) rely on a linearized collision term (**BGK, Bhatnagar-Gross-Krook approximation**)

$$\mathcal{Q} \approx \frac{1}{\tau_r}(f - f_{eq})$$

All these methods require the prior knowledge of the equilibrium distribution!

The Boltzmann Equation is not only for rarefied gases!

- ▶ The flow regime of a granular gas depends on Knudsen number  $Kn = \frac{\lambda}{L_0}$
- ▶ The hydrodynamic description based on the Navier-Stokes-Fourier (NSF) equation is valid only for low  $Kn$ :
- ▶ Continuous regime ( $Kn < 0.01$ ): NSF with no-slip BC.
- ▶ Slip regime ( $0.01 < Kn < 0.1$ ): NSF and partial slip BC at walls.
- ▶ For  $Kn > 0.1$ : Full Boltzmann equation.



*Adapted from: G. A. Bird (1994)*

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- ▶ MOM originates in kinetic theory of gases<sup>4</sup>:  $n(t, x, U)$
- ▶ The moment of order zero is related to the density:

$$\rho(t, x) \equiv m M_{0,0,0}(t, x) = m \iiint_{-\infty}^{+\infty} n(t, x, U) dU$$

- ▶ The moment of order one is used to define the average velocity:

$$\langle U \rangle = \left( \frac{M_{1,0,0}}{M_{0,0,0}}, \frac{M_{0,1,0}}{M_{0,0,0}}, \frac{M_{0,0,1}}{M_{0,0,0}} \right)$$

- ▶ By applying the MOM to the Boltzmann equation, an infinite system of equations (cascade) appears
- ▶ Euler, Navier-Stokes and Burnett equations are obtained by with the Chapman-Enskog method (asymptotic expansions at different orders)

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<sup>4</sup>The same name however may refer to many different methods in different fields

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- ▶  $n(t, x, U_p, \xi_p, U_f, \xi_f)$ , represents the number of particles (per unit volume) with velocity equal to  $U_p$ , internal coordinate  $\xi_p$  and see a continuous phase with velocity  $U_f$  and internal coordinate  $\xi_f$ .
- ▶ The evolution of the NDF is dictated by the **GPBE**:

$$\begin{aligned} \frac{\partial n}{\partial t} + \frac{\partial}{\partial x} \cdot (U_p n) + \frac{\partial}{\partial U_p} \cdot [(A_{fp} + A_p) n] + \frac{\partial}{\partial \xi_p} \cdot (G_p n) \\ + \frac{\partial}{\partial U_f} \cdot [(A_{pf} + A_f) n] + \frac{\partial}{\partial \xi_f} \cdot (G_f n) = \mathcal{Q} \quad (1) \end{aligned}$$

- ▶ phase-space velocity for particle velocity:  $A_{fp} + A_p$  (**average particle acceleration** → acceleration model (drag, lift, ...))
- ▶ phase-space velocity for particle internal coordinate:  $G_p$  (e.g. **particle growth rate**)
- ▶ Discontinuous jump term:  $\mathcal{Q}$  (e.g. **particle collision**, aggregation, breakage, nucleation, etc.)



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Generalized Population Balance Equation can be used for various applications

- ▶ Poly-dispersed<sup>5</sup> multiphase flows
- ▶ Bubbly flows, Particle-laden flows
- ▶ Granular flows, fluidized beds
- ▶ Rarefied gases

Classical CFD models such as Mixture model, two-fluid model can be recovered

In general the idea of quadrature-based moment methods (QBMM) can be used for generic kinetic/PDF equations

- ▶ Statistical description of turbulence and turbulent reactive flows (Pope)
- ▶ Mean field limit in models of social behavior (crowd, swarms, traffic, opinion)
- ▶ Mean field equations of stochastic processes
- ▶ Fokker-Planck equation

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<sup>5</sup>Fluid or solid particles of different size immersed in a continuous fluid phase

The mesoscale/kinetic models are highly dimensional (1 time + 3 spatial coordinates + 1 size + 3 velocities + ... )

## A plethora of methods have been generated:

- ▶ Interesting ways to solve it are **Lagrangian / Monte Carlo methods (DSMC)** or to **high-dimensional adaptive DG** methods
- ▶ In PBE the distribution is often discretized into classes or sections (FD)
- ▶ Widely used among practitioners in multiphase CFD is the **multiple-size-group (MUSIG) method**
- ▶ For the BE it is equivalent to the **discrete-velocity method**
- ▶ **The method of moments (MOM)** has been used for the solution of both PBE and BE, but the resulting closure problem is overcome by different strategies (e.g. Grad method, other functional assumptions, method of moments with interpolative closure, MOMIC)

- ▶ Important advantage is that the 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**
- ▶ The **closure problem** is the impossibility of writing a term as a function of a finite set of moments
- ▶ When the kinetic equation contains a derivative with respect to an internal variable, we have a **cascade of equations for the moments** ( $M_i$  depends on  $M_{i+1}$ )
- ▶ Often integral source terms also need closure

The issues of the number of moments to be tracked and the closure adopted both affect overall accuracy  $\Rightarrow$  connected and addressed together

When applying the moment transform (i.e. integral) closures must be assumed

## THE CLOSURE PROBLEM APPEARS ALWAYS IN THE FOLLOWING FORM:

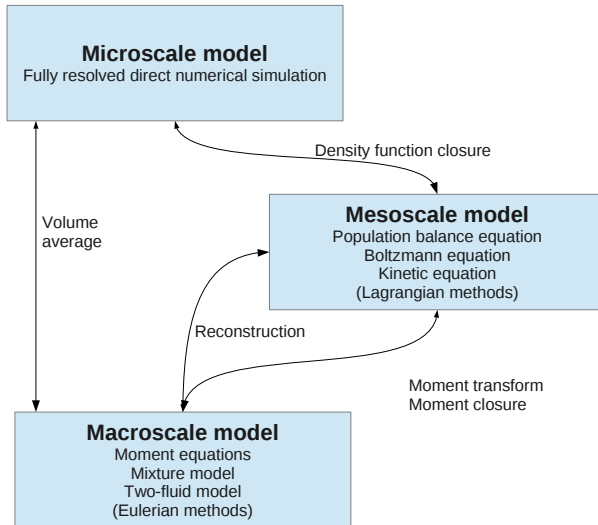
$$I = \int_{\Omega_\xi} g(\xi)n(\xi) d\xi, \quad (2)$$

where  $n(\xi)$  is the univariate NDF to be approximated and  $g$  a generic function to be closed

## PRESUMED-PDF APPROACHES

- ▶ A possible approach is to simply to assume a shape for the PDF/NDF
- ▶ This is reasonable when there is a fast relaxation towards equilibrium (e.g., in Boltzmann equations the Maxwellian equilibrium is a Gaussian)
- ▶ There are many cases when the actual NDF is far from equilibrium
- ▶ How to find the best closure?

# The problem is multiscale in nature!



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- The closure problem can be overcome by using the following quadrature formula:

$$\int_{\Omega_\xi} n(\xi) g(\xi) d\xi \approx \sum_{\alpha=1}^N w_\alpha g(\xi_\alpha), \quad (3)$$

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

- The degree of accuracy is equal to  $d$  if the interpolation 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 the interpolation formula inexact.



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## QBMM USE A GAUSSIAN QUADRATURE

The NDF is the weight function or measure; the moments

$$M_k = M(k) = \langle \xi^k \rangle = \int_{\Omega_\xi} n(\xi) \xi^k d\xi, \quad k = 0, 1, 2, \dots \quad (5)$$

are used to compute a Gaussian quadrature rule with a degree of accuracy of  $2N - 1$ .

A set of polynomials  $\{P_0(\xi), P_1(\xi), \dots, P_\alpha(\xi), \dots\}$  with  $P_\alpha(\xi) = k_{\alpha,0}x^\alpha + k_{\alpha,1}x^{\alpha-1} + \dots + k_{\alpha,\alpha}$ , is said to be orthogonal in the integration interval  $\Omega_\xi$ , with respect to the weight function, if

$$\int_{\Omega_\xi} n(\xi) P_\alpha(\xi) P_\beta(\xi) d\xi \begin{cases} = 0 & \text{for } \alpha \neq \beta, \\ > 0 & \text{for } \alpha = \beta, \end{cases} \quad (6)$$

and, of course, is said to be orthonormal if

$$\int_{\Omega_\xi} n(\xi) P_\alpha(\xi) P_\beta(\xi) d\xi = \begin{cases} 0 & \text{for } \alpha \neq \beta, \\ 1 & \text{for } \alpha = \beta. \end{cases} \quad (7)$$

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

$$P_{\alpha+1}(\xi) = (\xi - a_\alpha)P_\alpha(\xi) - b_\alpha P_{\alpha-1}(\xi), \quad \alpha = 0, 1, 2, \dots \quad (8)$$

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

$$a_\alpha = \frac{\int_{\Omega_\xi} n(\xi) \xi P_\alpha(\xi) P_\alpha(\xi) d\xi}{\int_{\Omega_\xi} n(\xi) P_\alpha(\xi) P_\alpha(\xi) d\xi}, \quad \alpha = 0, 1, 2, \dots \quad (9)$$

$$b_\alpha = \frac{\int_{\Omega_\xi} n(\xi) P_\alpha(\xi) P_\alpha(\xi) d\xi}{\int_{\Omega_\xi} n(\xi) P_{\alpha-1}(\xi) P_{\alpha-1}(\xi) d\xi}, \quad \alpha = 1, 2, \dots \quad (10)$$

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

- ▶ The coefficients  $a_\alpha$  and  $b_\alpha$  can be written in terms of the moments
- ▶ The coefficients necessary for the construction of a polynomial of order  $N$  can be calculated from the first  $2N - 1$  moments of the NDF
- ▶ For example with  $M_0$ ,  $M_1$ ,  $M_2$  and  $M_3$ , it is possible to calculate the following coefficients:

$$\begin{aligned}a_0 &= \frac{M_1}{M_0}, \\a_1 &= \frac{M_3 M_0^2 + M_1^3 - 2M_2 M_1 M_0}{M_2 M_0 + M_1^2 - 2M_1^2 M_0}, \\b_1 &= \frac{M_2 M_0 + M_1^2 - 2M_1^2 M_0}{M_0^2},\end{aligned}\tag{11}$$

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

## GAUSSIAN QUADRATURE

The necessary and sufficient condition for the following formula:

$$\int_{\Omega_{\xi}} n(\xi)g(\xi) \, d\xi = \sum_{\alpha=1}^N g(\xi_{\alpha})w_{\alpha} + R_N(g), \quad (12)$$

to be a Gaussian quadrature approximation is that its nodes  $\{\xi_{\alpha}\}$  coincide with the  $N$  roots of the polynomial  $P_N(\xi)$  of order  $N$  orthogonal in  $\Omega_{\xi}$  with respect to the weight function  $n(\xi)$ .

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- ▶ McGraw (1997) introduced the Quadrature Method Of Moments (QMOM) in the context of Population Balance Equation
- ▶ Marchisio and Fox (2005) developed the Direct Quadrature Method of Moments (DQMOM) that became very popular in the Chemical Engineering community because very **easy to implement in CFD codes**
- ▶ Different extensions to **multivariate** cases have been proposed. The more general one is the Conditional QMOM (CQMOM) (Yuan and Fox, 2011)
- ▶ Kernel density type reconstruction have been incorporated in QMOM with the Extended QMOM (EQMOM) (Yuan, Laurent, Fox, 2012)
- ▶ Different applications have been studied: particulate processes, dispersed flows (gas-liquid, gas-solid, fluid-solid), turbulent micro-mixing, rarefied gases, generic kinetic/Fokker-Planck equations, non-linear filtering, ...
- ▶ Recently proposed for **Uncertainty Quantification** (Passalacqua and Fox, 2012; Attar and Vedula, 2012)
- ▶ A large number of variants have been proposed (FCMOM, TBMM, DuQMoGeM, SQMOM , ...)

All the closures based on Gaussian quadratures computed directly from moments took the name of **QUADRATURE-BASED MOMENT METHODS (QBMM)**

- ▶ For **univariate problems** things are simple: with **QMOM**, transport equations for the first  $2N$  moments are solved, the closure problem is overcome by using a quadrature approx.
- ▶ The quadrature is very accurate in approximating integrals of smooth functions in which the NDF appears (such as the collision integrals)
- ▶ The method implicitly assumes that the NDF is a summation of Dirac delta functions centered on the nodes and weighted by the weights of the quadrature approximation
- ▶ The quadrature approximation of order  $N$  is calculated from the first  $2N$  moments with direct inversion algorithms: **product-difference** or **Wheeler algorithms**



## HOW DO WE COMPUTE THE GAUSSIAN QUADRATURE APPROX?

The  $N$  weights and  $N$  abscissas can be determined by solving the following non-linear system:

$$\begin{aligned} M_0 &= \sum_{\alpha=1}^N w_{\alpha}, \\ &\vdots \\ M_{2N-1} &= \sum_{\alpha=1}^N w_{\alpha} \xi_{\alpha}^{2N-1}. \end{aligned} \tag{13}$$

using the Newton-Raphson method, or any other non-linear equation solver (very expensive, ill-posed and very good initial guess needed)

Much more efficient are the **product-difference** or **Wheeler algorithms**

- Let us consider the following example (continuous rate of change of the internal coordinate  $\dot{\xi} = G_p$ ):

$$\frac{Dn}{Dt} = S = -\frac{\partial}{\partial \xi} (G_p n) + h, \quad (14)$$

- We solve transport equations for the moment set:

$$\frac{DM_k}{Dt} = \bar{S}_k, \quad (15)$$

with  $k = 0, 1, 2, \dots, 2N - 1$  and with an initial condition

$$M_k(0) = \int_{\Omega_\xi} n(0, \xi) \xi^k d\xi$$

- Integration of the system requires the evaluation of the source term through the quadrature approximation

- Moment equations

$$\frac{DM_k}{Dt} = k \int_0^\infty \langle G_p | \xi \rangle \xi^{k-1} n(\xi) d\xi \quad (16)$$

- The closure problem is overcome as follows:

$$\frac{DM_k}{Dt} = k \sum_{\alpha=1}^N \langle G_p | \xi_\alpha \rangle (\xi_\alpha)^{k-1} w_\alpha \quad (17)$$

- where as already mentioned weights  $w_\alpha$  and nodes  $\xi_\alpha$  are calculated from the PD or Wheeler algorithm from the moments
- This method is called **Quadrature Method of Moments** (the variables are the moments)

In the case of standard nucleation, (positive) growth, growth dispersion, aggregation and breakage, application of QBMM to the source term yields

$$\begin{aligned} \frac{DM_k}{Dt} = & \bar{J}_k + k \sum_{\alpha=1}^N \xi_{\alpha}^{k-1} G_{\alpha} w_{\alpha} + k(k-1) \sum_{\alpha=1}^N \xi_{\alpha}^{k-2} D_{\alpha} w_{\alpha} \\ & + \frac{1}{2} \sum_{\alpha=1}^N \sum_{\gamma=1}^N [(\xi_{\alpha} + \xi_{\gamma})^k - \xi_{\alpha}^k - \xi_{\gamma}^k] \beta_{\alpha,\gamma} w_{\alpha} w_{\gamma} + \sum_{\alpha=1}^N b_{\alpha} \bar{N}_{\alpha}^k w_{\alpha} - \sum_{\alpha=1}^N \xi_{\alpha}^k b_{\alpha} w_{\alpha} \end{aligned}$$

where  $G_{\alpha} = \langle G_p | \xi_{\alpha} \rangle$ ,  $D_{\alpha} = D(\xi_{\alpha})$ ,  $\beta_{\alpha,\gamma} = \beta(\xi_{\alpha}, \xi_{\gamma})$  and  $b_{\alpha} = b(\xi_{\alpha})$  and the moments of the daughter distribution function are  $\bar{N}_{\alpha}^k = \int \xi^k N(\xi | \xi_{\alpha}) d\xi$ .

- The fact that the closure problem is overcome with the quadrature approximation:

$$\int_{\Omega_{\xi}} n(\xi) g(\xi) d\xi \approx \sum_{\alpha=1}^N w_{\alpha} g(\xi_{\alpha}), \quad (19)$$

- Is equivalent to the assumption that the NDF is as follows:

$$n(\xi) = \sum_{\alpha=1}^N w_{\alpha} \delta(\xi - \xi_{\alpha}), \quad (20)$$

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

- Assuming that the weights and nodes are **differentiable in space/time** the following transport equation is obtained:

$$\sum_{\alpha=1}^N \delta(\xi - \xi_{\alpha}) \left( \frac{Dw_{\alpha}}{Dt} \right) - \sum_{\alpha=1}^N \delta'(\xi - \xi_{\alpha}) \left( w_{\alpha} \frac{D\xi_{\alpha}}{Dt} \right) = S(\xi), \quad (21)$$

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

$$\begin{aligned} \sum_{\alpha=1}^N \delta(\xi - \xi_{\alpha}) \left( \frac{Dw_{\alpha}}{Dt} \right) - \sum_{\alpha=1}^N \delta'(\xi - \xi_{\alpha}) \left( -\xi_{\alpha} \frac{Dw_{\alpha}}{Dt} + \frac{D\varsigma_{\alpha}}{Dt} \right) \\ = S(\xi). \end{aligned} \quad (22)$$

- We now define  $a_\alpha$  and  $b_\alpha$  to be the source terms:

$$\frac{Dw_\alpha}{Dt} = a_\alpha, \quad \frac{D\zeta_\alpha}{Dt} = b_\alpha. \quad (23)$$

- Using these definitions Eq. (22) can be rewritten in a simpler form:

$$\sum_{\alpha=1}^N [\delta(\xi - \xi_\alpha) + \delta'(\xi - \xi_\alpha)\xi_\alpha] a_\alpha - \sum_{\alpha=1}^N \delta'(\xi - \xi_\alpha) b_\alpha = S(\xi). \quad (24)$$

- This equation can now be used to determine the unknown functions  $a_\alpha$  and  $b_\alpha$  by applying the moment transformation.

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

$$\begin{aligned}\int_{-\infty}^{+\infty} \xi^k \delta(\xi - \xi_\alpha) d\xi &= (\xi_\alpha)^k, \\ \int_{-\infty}^{+\infty} \xi^k \delta'(\xi - \xi_\alpha) d\xi &= -k(\xi_\alpha)^{k-1},\end{aligned}\tag{25}$$

- The moment transform of Eq. (24) yields

$$(1 - k) \sum_{\alpha=1}^N \xi_\alpha^k a_\alpha + k \sum_{\alpha=1}^N \xi_\alpha^{k-1} b_\alpha = \bar{S}_k,\tag{26}$$

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



- The linear system in Eq. (26) can be written in matrix form:

$$A\alpha = d. \quad (27)$$

where

$$\alpha = [a_1 \quad \cdots \quad a_N \quad b_1 \quad \cdots \quad b_N]^T = \begin{bmatrix} a \\ b \end{bmatrix}, \quad (28)$$

$$d = [\bar{S}_{k_1} \quad \cdots \quad \bar{S}_{k_{2N-1}}]^T, \quad (29)$$

- The components of the matrix  $A$  are

$$a_{ij} = \begin{cases} (1 - k_i) \xi_j^{k_i} & \text{if } 1 \leq j \leq N, \\ k_i \xi_j^{k_i-1} & \text{if } N + 1 \leq j \leq 2N. \end{cases} \quad (30)$$

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

$$A = \begin{bmatrix} 1 & \dots & 1 & 0 & \dots & 0 \\ 0 & \dots & 0 & 1 & \dots & 1 \\ -\xi_1^2 & \dots & -\xi_N^2 & 2\xi_1 & \dots & 2\xi_N \\ \vdots & & \vdots & \vdots & & \vdots \\ 2(1-N)\xi_1^{2N-1} & \dots & 2(1-N)\xi_N^{2N-1} & (2N-1)\xi_1^{2N-2} & \dots & (2N-1)\xi_N^{2N-2} \end{bmatrix}$$

- $A$  does not depend on the weights  $w_\alpha$  and if the abscissas  $\xi_\alpha$  are unique, then  $A$  will be full rank.

- ▶ This method is called **Direct quadrature method of moments** and follows this procedure:
- ▶ The evolution equations for weights and nodes of the quadrature approximation are solved:

$$\frac{Dw_{\alpha}}{Dt} = a_{\alpha}, \quad \frac{Dw_{\alpha}\xi_{\alpha}}{Dt} = b_{\alpha}. \quad (32)$$

- ▶ The source terms are calculated by inverting the linear system and by using the following initial condition:

$$w_{\alpha}(0) = w_{\alpha}^0, \quad \varsigma_{\alpha}(0) = w_{\alpha}^0 \xi_{\alpha}^0 \quad \text{for } k = 1, \dots, N. \quad (33)$$

in turn calculated from the initial moments

- ▶ QMOM & DQMOM are very accurate in tracking the evolution of the moments of the NDF: 4-8 moments do the same job of many (e.g. 100) classes or sections (see for example the work of [Marchisio et al., 2003](#) and [Vanni, 2000](#))
- ▶ The Wheeler algorithm is very robust (if the moments are realizable) and for particular cases the Wheeler algorithm is successful when PD fails
- ▶ QMOM & DQMOM are identical for spatially homogeneous systems (if the nodes are distinct and if the problem is continuous in time)
- ▶ Important differences arise when treating spatially inhomogeneous systems (discussed next)
- ▶ In general increasing the number of nodes of the quadrature approximation and of moments to be tracked increases the accuracy
- ▶ Problems can appear when kernels and NDFs are discontinuous or when they are localized in the phase-space (e.g. fine dissolution)

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## Applications

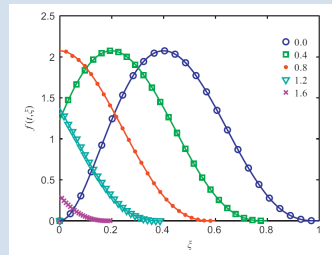
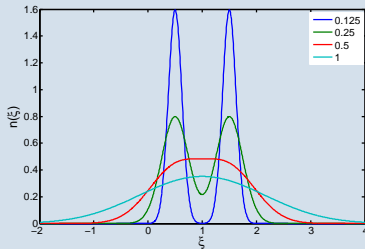
- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
- Porous media
- UQ and other applications

- ▶ only integral representation, no localized processes in phase space, smoothness of kernels  $\beta, G, \dots$
- ▶ It fails in the computation of the entropy  $\int_{\Omega_\xi} f \log f d\xi$
- ▶ However smooth basis functions can be used instead of delta functions (Extended Quadrature Method of Moments, EQMOM)
- ▶ PDF reconstructed as a mixture of Gaussians (or other distributions) like the Kernel Density Estimation
- ▶ The choice of basis functions can be done arbitrarily or with additional unknown parameters (e.g., mean and variance of normal distribution)
- ▶ Additional parameters must be found by additional equations (i.e., more moments must be solved)
  - The inversion problems can become difficult to solve

An alternative is the reconstruction through **Maximum Entropy Method** or the reconstruction through the orthogonal polynomials

REMARK: An underlying kinetic representation and the reconstruction of the PDF of the velocity are also the basis of the so-called **Kinetic schemes** and **Asymptotic Preserving schemes** (see very interesting works of S. Jin, P. Degond, ...)

## EQMOM for a dissolution problem GAUSSIAN DISTR. SOLUTION WITH $N = 4$ BETA DISTR.



a

<sup>a</sup>Yuan, C., Laurent, F., Fox, R.O. An extended quadrature method of moments for population balance equations (2012) Journal of Aerosol Science, 51, pp. 1-23.

$$\delta_{\sigma} = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\xi - \xi_{\alpha})^2}{2\sigma^2}\right); \delta_{\sigma} = \frac{\xi^{\frac{\xi_{\alpha}}{\sigma}-1} (1-\xi)^{\frac{(1-\xi_{\alpha})}{\sigma}-1}}{B(\xi_{\alpha}, \sigma)}$$

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The original multiivariate GPBE for  $M$ -dimensional phase space:

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial x} \cdot (U_p n) = \frac{\partial}{\partial x} \cdot \left( D \frac{\partial n}{\partial x} \right) - \frac{\partial}{\partial \xi} \cdot (G n) + Q, \quad (34)$$

is solved with **DQMOM** with the following  $(M + 1)N$  equations:

$$\frac{\partial w_\alpha}{\partial t} + \frac{\partial}{\partial x} \cdot (U_{p,\alpha} w_\alpha) = \frac{\partial}{\partial x} \cdot \left( D_\alpha \frac{\partial w_\alpha}{\partial x} \right) + a_\alpha, \quad (35)$$

$$\frac{\partial w_\alpha \xi_\alpha}{\partial t} + \frac{\partial}{\partial x} \cdot (U_{p,\alpha} w_\alpha \xi_\alpha) = \frac{\partial}{\partial x} \cdot \left( D_\alpha \frac{\partial w_\alpha \xi_\alpha}{\partial x} \right) + b_\alpha \quad (36)$$

with  $\alpha \in 1, \dots, N$  and where the source terms are calculated by solving the following linear system:

$$\begin{aligned} \sum_{\alpha=1}^N \left[ \left( 1 - \sum_{\beta=1}^M k_\beta \right) \prod_{\beta=1}^M \xi_{\beta,\alpha}^{k_\beta} \right] a_\alpha + \sum_{\alpha=1}^N \sum_{\beta=1}^M \frac{\partial}{\partial \xi_{\beta,\alpha}} \left( \prod_{\gamma=1}^M \xi_{\gamma,\alpha}^{k_\gamma} \right) b_{\beta,\alpha} \\ = \sum_{\alpha=1}^N \sum_{\beta=1}^M \sum_{\gamma=1}^M \frac{\partial^2}{\partial \xi_{\beta,\alpha} \partial \xi_{\gamma,\alpha}} \left( \prod_{\delta=1}^M \xi_{\delta,\alpha}^{k_\delta} \right) + \bar{\mathcal{S}}_{k_1, \dots, k_M}, \end{aligned} \quad (37)$$

Whereas with **QMOM** after having defined a generic moments :

$$M_k \equiv \int_{\Omega_\xi} \xi_1^{k_1} \dots \xi_M^{k_M} n(t, \xi) d\xi \quad (38)$$

equivalent notations  $M_{k_1, \dots, k_M} = M_k = M(k_1, \dots, k_M) = M(k)$ , we solve the resulting transport equations:

$$\begin{aligned} \frac{\partial M_k}{\partial t} + \frac{\partial}{\partial x} \cdot (U_p^k M_k) - \frac{\partial}{\partial x} \cdot \left( D^k \frac{\partial M_k}{\partial x} \right) = \bar{S}_k = \\ \int_{\Omega_\xi} \xi^k \left[ -\frac{\partial}{\partial \xi} \cdot (\langle G_p | \xi \rangle n) + S \right] d\xi \end{aligned} \quad (39)$$

and the closure problem is overcome by using the quadrature approximation.

For **multivariate problems**  $N(M + 1)$  moments (**optimal moment set**) are used to determine the quadrature approximation

**Brute-force QMOM**: direct solution of the following non-linear system

$$M_{k_{i1}, k_{i2}, \dots, k_{iM}} = M(k_i) = \sum_{\alpha=1}^N w_{\alpha} \prod_{\beta=1}^M \xi_{\beta, \alpha}^{k_{i\beta}}, \quad 1 \leq i \leq N(M + 1)$$

by employing the Newton-Raphson iterative scheme:

$$Z_{n+1} = Z_n - A^{-1}(K, X_n)F(Z_n).$$

The Jacobian  $A$  is identical to the matrix of the linear system of **DQMOM**!

Alternatively the **Tensor-Product QMOM** can be used

- ▶ To perform calculations with both multivariate QMOM<sup>6</sup> and DQMOM the matrix  $A$  must be non-singular (or full rank)
- ▶ For  $M = 1$  (univariate) problems this requirement is satisfied if the nodes are distinct
- ▶ For multivariate cases, having distinct abscissas does not guarantee that  $A$  will be full rank
- ▶ It can be shown that for fixed  $N$  and  $M$ , certain distinct moments are linearly dependent when  $M \geq 1$  for all possible sets of abscissas
- ▶ It is therefore necessary to identify a moment set for which  $A$  is always non-singular for all non-degenerate points in phase space for given values of  $M$  and  $N$ .
- ▶ This definition is useful also when other inversion algorithms are used (e.g. **Tensor-Product QMOM**)

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<sup>6</sup>If the Brute-Force inversion algorithm is used.

## OPTIMAL MOMENT SET

1. An optimal moment set consists of  $N(M + 1)$  distinct moments.
2. An optimal moment set will result in a full-rank square matrix  $A$  for all possible sets of  $N$  distinct, non-degenerate abscissas.
3. An optimal moment set includes all linearly independent moments of a particular order  $\gamma_i$  before adding moments of higher order.
4. An optimal moment set must result in a perfectly symmetric treatment of the internal coordinates.

**Table:** Moments used to build a bivariate quadrature approximation ( $M = 2$ ) for  $N = 2$ . In this case  $M_{0,3}$  is chosen as the third-order moment to saturate the degrees of freedom.

M(2,0)			
M(1,0)			
M(0,0)	M(0,1)	M(0,2)	M(0,3)

**Table:** Moments used to build a bivariate quadrature approximation ( $M = 2$ ) for  $N = 3$ . In this case  $M_{2,1}$ ,  $M_{1,2}$  and  $M_{0,3}$  are chosen among the third-order moments to saturate the degrees of freedom.

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)

**Table:** Optimal moment set used to build a bivariate quadrature approximation ( $M = 2$ ) for  $N = 4$ . Only when  $N^{1/M}$  is an integer, there exists an optimal moment set (that fulfills the symmetry requirement).

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)

**Table:** Optimal moment set used to build a 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)

- 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  $2N_1 - 1$ :

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

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

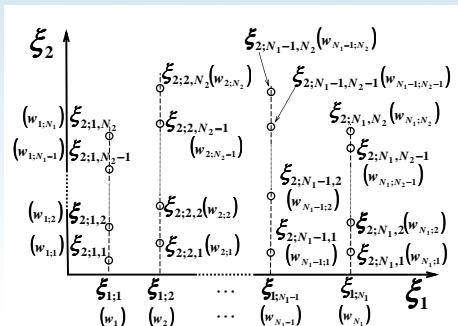
- The generic moment becomes:

$$\begin{aligned} M_{k_1, k_2} &= \iint n(\xi_1, \xi_2) \xi_1^{k_1} \xi_2^{k_2} d\xi_1 d\xi_2 \\ &= \sum_{\alpha_1=1}^{N_1} w_{\alpha_1} \xi_{1;\alpha_1}^{k_1} \int f_{21}(\xi_2 | \xi_{1;\alpha_1}) \xi_2^{k_2} d\xi_2 \end{aligned}$$

- **Conditional moment**:  $\left\langle \xi_2^{k_2} \right\rangle_{\alpha_1} = \int f_{12}(\xi_2 | \xi_{1;\alpha_1}) \xi_2^{k_2} d\xi_2$



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**



**Table:** 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)

Bivariate Gaussian distr. with  $\rho = 0.0$  and  $N = 9$ ; **BF-QMOM** (diamond),  
**TP-QMOM** (circle) and **CQMOM** (square)

Bivariate Gaussian distr. with  $\rho = 0.5$  and  $N = 9$ ; **BF-QMOM** (diamond),  
**TP-QMOM** (circle) and **CQMOM** (square)

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- The spatially inhomogeneous GPBE operating on  $n(\xi)$  reads as follows:

$$\frac{\partial n}{\partial t} + \frac{\partial}{\partial x} \cdot (\langle U_p | \xi \rangle n) = \frac{\partial}{\partial x} \cdot \left( D(\xi) \frac{\partial n}{\partial x} \right) - \frac{\partial}{\partial \xi} (\langle G_p | \xi \rangle n) + \mathcal{S} \quad (40)$$

- The application of the moment transform,  $M_k = \int n(\xi) \xi^k d\xi$ , generates **several closure problems**:

$$\frac{\partial M_k}{\partial t} + \frac{\partial}{\partial x} \cdot (U_p^k M_k) = \frac{\partial}{\partial x} \cdot \left( D^k \frac{\partial M_k}{\partial x} \right) + \bar{S}_k \quad (41)$$

where of course  $U_p^k = \frac{\int \langle U_p | \xi \rangle n(\xi) \xi^k d\xi}{M_k}$  (similarly  $D^k$ ) and

$$\bar{S}_k = \int \left( \frac{\partial}{\partial \xi} (\langle G_p | \xi \rangle n) + \mathcal{S} \right) \xi^k d\xi.$$

- The solution with QMOM is as usual ...

- From  $\{M_0, M_1, \dots, M_{2N-1}\}$  the Gaussian quadrature with  $N$  nodes is constructed resulting in the following approximation

$$M_k(t, x) = \int_{\Omega_\xi} n(t, x, \xi) \xi^k d\xi \approx \sum_{\alpha=1}^N w_\alpha(t, x) (\xi_\alpha(t, x))^k \quad (42)$$

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

$$U_p^k(t, x) = \frac{\int_{\Omega_\xi} \langle U_p | \xi \rangle n(t, x, \xi) \xi^k d\xi}{M_k} \approx \frac{\sum_{\alpha=1}^N \langle U_p | \xi_\alpha \rangle w_\alpha \xi_\alpha^k}{M_k} \quad (43)$$

- By using different velocities,  $U_p^k(t, x)$ , for the different moments, we can describe mixing and segregation patterns

Moreover if  $w_\alpha$  and  $\xi_\alpha$  are continuous functions of space and time, DQMOM can also be applied (slightly different now due to the diffusion term):

$$\frac{\partial w_\alpha}{\partial t} + \frac{\partial}{\partial x} \cdot (\langle U_p | \xi_\alpha \rangle w_\alpha) = \frac{\partial}{\partial x} \cdot \left( D(\xi_\alpha) \frac{\partial w_\alpha}{\partial x} \right) + a_\alpha \quad (44)$$

$$\frac{\partial w_\alpha \xi_\alpha}{\partial t} + \frac{\partial}{\partial x} \cdot (\langle U_p | \xi_\alpha \rangle w_\alpha \xi_\alpha) = \frac{\partial}{\partial x} \cdot \left( D(\xi_\alpha) \frac{\partial w_\alpha \xi_\alpha}{\partial x} \right) + b_\alpha \quad (45)$$

with  $\alpha \in 1, \dots, N$  and where the source terms are as usual determined by solving the following linear system:

$$(1 - k) \sum_{\alpha=1}^N \xi_\alpha^k a_\alpha + k \sum_{\alpha=1}^N \xi_\alpha^{k-1} b_\alpha = \bar{S}_k + \bar{C}_k, \quad (46)$$

where

$$\bar{C}_k = k(k-1) \sum_{\alpha=1}^N \xi_\alpha^{k-2} C_\alpha, \quad C_\alpha = w_\alpha D \left( \frac{\partial \xi_\alpha}{\partial x} \cdot \frac{\partial \xi_\alpha}{\partial x} \right), \quad (47)$$



- A moment set is said to be **valid** or **realizable**, if the Hankel-Hadamard determinants are all non-negative:

$$\Delta_{k,l} = \begin{vmatrix} M_k & M_{k+1} & \cdots & M_{k+l} \\ M_{k+1} & M_{k+2} & \cdots & M_{k+l+1} \\ \vdots & \vdots & \ddots & \vdots \\ M_{k+l} & M_{k+l+1} & \cdots & M_{k+l+l} \end{vmatrix} \geq 0, \quad k = 0, 1, \quad l \geq 0 \quad (48)$$

for  $k = 0, 1$  and  $l \geq 0$ .

- For  $l = 1$  we get:

$$M_k M_{k+2} - M_{k+1}^2 \geq 0 \quad k = 0, 1, 2, \dots \quad (49)$$

which for  $k = 0$  becomes the constraint of positive variance

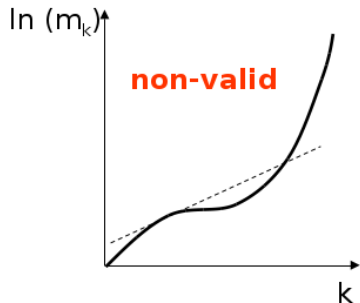
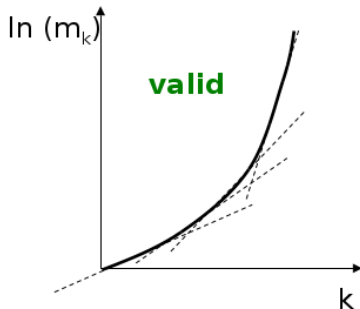
- Equivalently this becomes:

$$\frac{\mathbb{E}(M_k) + \mathbb{E}(M_{k+2})}{2} \geq \mathbb{E}(M_{k+1}) \quad k = 0, 1, 2, \dots; \quad (50)$$

or in other words convexity of the function  $\mathbb{E}(M_k)$  with respect to  $k$

Less stringent condition: convexity of function  $\ln(M_k)$  with respect to  $k$

$$m_k m_{k-2} - m_{k-1}^2 \geq 0$$

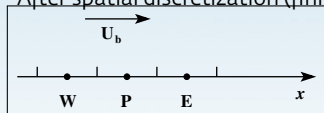


Ad-hoc correction algorithms are needed!

An alternative is to solve the transport equation for a generic moment  $M_k$  with discretization schemes that PRESERVE the moments ("**Realizable schemes**"):

$$\frac{\partial M_k}{\partial t} + u_p \frac{\partial M_k}{\partial x} = \bar{S}_k - u_p \frac{\partial M_k}{\partial x}$$

After spatial discretization (finite-volume):

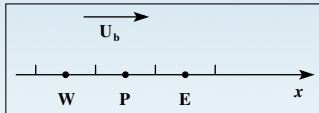


$$\frac{dM_k^P}{dt} = \bar{S}_k^P - \frac{u_p}{\Delta x} (M_k^E - M_k^W)$$

With first-order upwind  $M_k^E = M_k^P$  and  $M_k^W = M_k^W$

**Spatial discretization schemes based on first-order upwind always result in VALID moments. Higher-order schemes (CDS, second-order upwind, QUICK, MUSCL) can result in INVALID moments.**

- ▶ One solution would be to evaluate the moments at the faces  $M_k^e$  and  $M_k^w$  through the quadrature approximation
- ▶ We know the value of the moments at the center of the cells  $M_k^w, M_k^p, M_k^e$



- ▶ From these moments we can evaluate the corresponding weights  $w_\alpha^p$  and abscissas  $\xi_\alpha^p$
- ▶ If weights at the center of the face are interpolated with  $p^{\text{th}}$ -order spatial reconstruction and the abscissas are interpolated 1<sup>st</sup>-order spatial the resulting moments will be valid
- ▶ This allows to improve the numerical accuracy preserving the moments!
- ▶ Alternatively one can use semi-Lagrangian schemes (Attili and Bisetti, 2013)

- ▶ In QMOM the governing equations are for the moments that are 'conserved' variables
- ▶ In DQMOM the governing equations are for weights and weighted abscissas that are 'primitive' variables
- ▶ When QMOM is used (if proper discretization schemes are used) only the transported  $2N$  moments are preserved and conserved (and their linear combination)
- ▶ When DQMOM is used only weights and weighted abscissas are conserved and their linear combination:  $M_0$  and  $M_1$
- ▶ One disadvantage of DQMOM is that only two moments (of the  $2N$  selected) are conserved and saved from numerical errors!
- ▶ Another way to look at the problem is to consider that the equations in finite-volume codes are solved with an error called numerical diffusion whose coefficient is unknown!

- The **original DQMOM** requires the solution of these equations:

$$\begin{aligned}\frac{\partial w_\alpha}{\partial t} + U_p \frac{\partial w_\alpha}{\partial x} &= a_\alpha \\ \frac{\partial w_\alpha \xi_\alpha}{\partial t} + U_p \frac{\partial w_\alpha \xi_\alpha}{\partial x} &= b_\alpha \\ &\Downarrow \\ \frac{\partial M_k}{\partial t} + U_p \frac{\partial M_k}{\partial x} &= \bar{S}_k\end{aligned}$$

- When the finite-volume discretization is applied:

$$\begin{aligned}\frac{dw_\alpha^p}{dt} + \frac{U_p}{\Delta x} (w_\alpha^e - M_k^w) &= a_\alpha^p \\ \frac{d(w_\alpha \xi_\alpha)^p}{dt} + \frac{U_p}{\Delta x} ((w_\alpha \xi_\alpha)^e - (w_\alpha \xi_\alpha)^w) &= b_\alpha^p \\ &\Downarrow \\ \frac{dM_k^p}{dt} + \frac{U_p}{\Delta x} (M_k^e - M_k^w) &= \bar{S}_k^p\end{aligned}$$

failing in conserving higher-order moments ( $k \geq 2$ )

- Solution: fully conservative version of DQMOM (DQMOM-FC):

$$\begin{aligned}\frac{dM_k^p}{dt} &= -\frac{U_p}{\Delta x} (M_k^e - M_k^w) + \bar{S}_k^p \\ &\quad \Updownarrow \\ \frac{dw_\alpha^p}{dt} &= -a_{c,\alpha}^p + a_\alpha^p \\ \frac{d(w_\alpha \xi_\alpha)^p}{dt} &= -b_{c,\alpha}^p + b_\alpha^p\end{aligned}$$

now successfully conserving all the moments of the NDF

- Alternatively one can use semi-Lagrangian schemes (Attili and Bisetti, 2013)
- Summarizing if the equations for the moments have large physical diffusion terms DQMOM can be safely used (numerical diffusion will be smaller than real diffusion and the solution will contain no discontinuities and no shocks)
- When only the equation for the moments do not contain any physical diffusion term than DQMOM-FC should be used

## Kinetic and PDF equations

- Smoluchowski coagulation equation
- Population balance equation (PBE)
- Boltzmann equation (BE)
- Method of Moments
- Generalized population balance equation (GPBE)

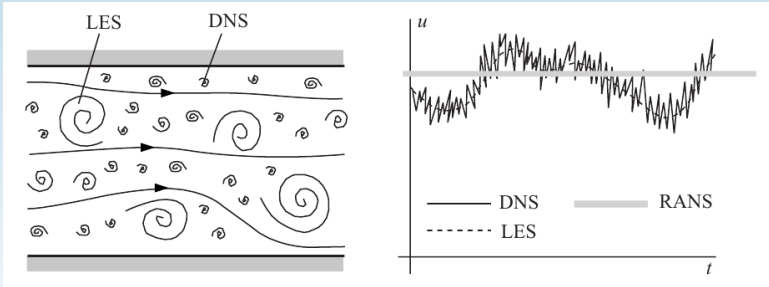
## Quadrature-based moment methods

- Numerical Methods and Closure problem
- Gaussian quadrature
- QMOM and DQMOM
- EQMOM
- Multivariate case
- Implementation in CFD codes / spatial inhomogeneity

## Applications

- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
- Porous media
- UQ and other applications





## DIRECT NUMERICAL SIMULATION (DNS)

All the flow-scales are solved without model  $\Rightarrow$  virtual experiments (3D and unsteady)

## LARGE EDDY SIMULATION (LES)

Equations are filtered in space (or frequency). Bigger 3D unsteady scales are solved; smaller ones are modelled with **sub-grid scale (SGS) models**

## RANS

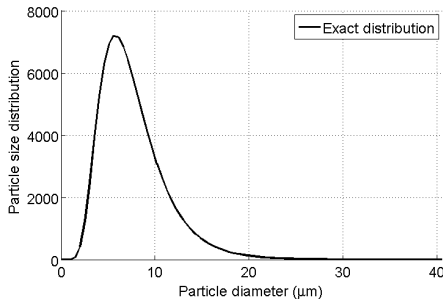
Time-averaged equations  $\Rightarrow$  only the mean flow is predicted

# Poly-dispersed particles

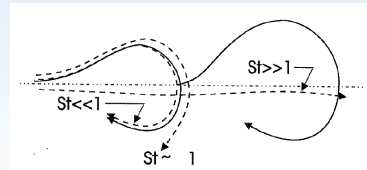
Particle Size Distribution (PSD) and Population Balance Eq. (PBE)

Particle Size Distribution

$$n(L; x, t) = \int_{\mathbb{R}^3} n(L, U_p; x, t) dU_p$$



$$St = \frac{\tau_p}{\tau_f} \approx \frac{\rho_p D^2}{18\mu\tau_f}$$

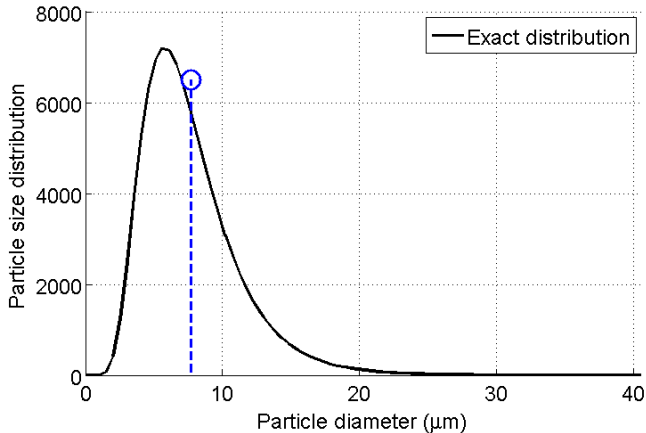


Particles of different size behave very differently with a non-linear relation between size and relative velocity

# Poly-dispersed particles

Log-normal PSD and QBMM approximation

Quadrature-based Moment Method (QBMM)  
nodes and weights to approximate  $f(L)$

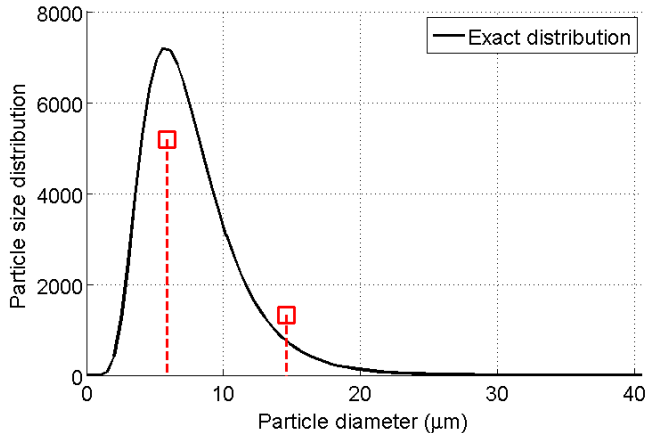


2 moments  $\rightarrow$  1 node, 1 weight  
Mean size

# Poly-dispersed particles

Log-normal PSD and QBMM approximation

Quadrature-based Moment Method (QBMM)  
nodes and weights to approximate  $f(L)$

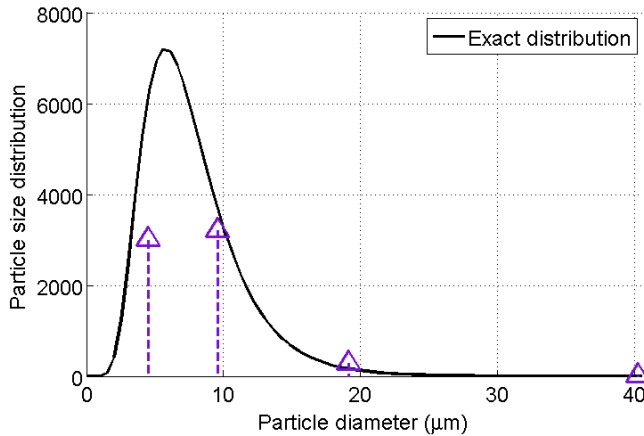


4 moments  $\rightarrow$  2 nodes, 2 weights  
Volume fraction

# Poly-dispersed particles

Log-normal PSD and QBMM approximation

Quadrature-based Moment Method (QBMM)  
nodes and weights to approximate  $f(L)$



8 moments  $\rightarrow$  4 nodes, 4 weights

## Population balance equation:

$$\partial_t n + \partial_x \langle U_p | L \rangle n + \cancel{\partial_L n G} \overset{\text{no growth term}}{=} \cancel{Q(n, n)} \overset{\text{no aggregation, breakage, nucleation}}{=}$$

Models for conditional velocity  $\langle U_p | L \rangle = U_p(L)$

### PSEUDO-HOMOGENEOUS MODEL, $St \ll 1$

Particles flow with fluid velocity  $U_p(L) = U$

### ALGEBRAIC MODELS (MIXTURE), $St \leq 1$

$U_p(L)$  is calculated with algebraic relations from the knowledge of  $U$

### DIFFERENTIAL MODELS (MULTI-FLUID), $St > 1$

$U_p(L)$  is solved with a momentum balance equation

- ▶ similar to the classical Algebraic Slip Model
- ▶ expansion of Maxey-Riley equation for small particle response time  $\tau_p$

$$U_p \approx U + O(\tau_p) \Rightarrow U_p - U = -\tau_p \left( \frac{DU}{Dt} - g \right)$$

- ▶ 1<sup>st</sup> order correction

$$U_p - U = -\tau_p (I + \tau_p \nabla U^T)^{-1} \left( \frac{DU}{Dt} - g \right)$$

- ▶ High  $Re_p$  effects considered using a modified  $\tau_p^*$
- ▶ can be extended to take into account other forces and two-way coupling

In Large Eddy Simulation (LES) we have only **filtered velocity field**  $\bar{U}$

## **APPROXIMATE DECONVOLUTION METHOD (ADM)**

To estimate the "real" unfiltered velocity we use an **approximate inverse filter**

$$U_i^* = \sum_{k=0}^{N_c} (I - G)^k \bar{U}_i$$

- ▶  $G$  is a test filter
- ▶  $N_c$  is the deconvolution order
- ▶ if  $N_c = 1$  it is like an inverse dynamic model
- ▶ considered  $N_c = 1, 5$  with Gaussian weights



- ▶ Single momentum equation for the mixture
- ▶ Equilibrium model to calculate velocity  $U_p(L)$
- ▶ Population balance discretized with Quadrature-Based Moment Method (QBMM)
- ▶ Solved directly in terms of nodes  $L_i$  and weights  $w_i$  (DQMOM formulation)

### SINGLE VELOCITY MODEL

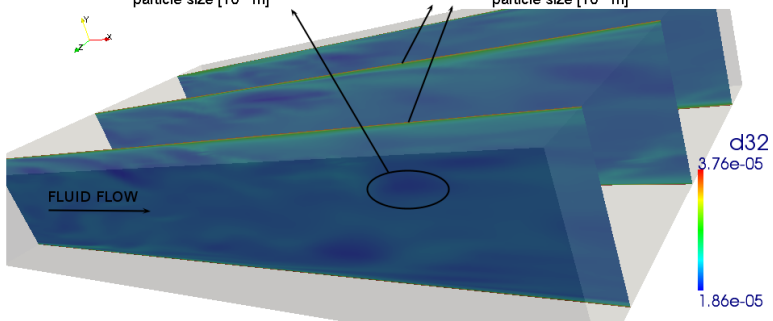
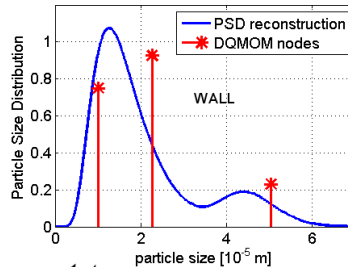
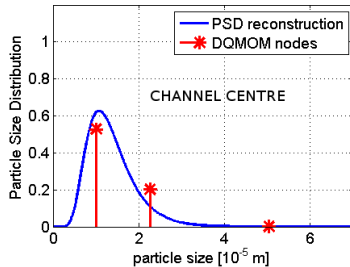
All particles flow with an overall mean velocity  $U_p(L) = U_p(\bar{L})$

### MULTIPLE VELOCITIES MODEL

Each node (particle class) considered as a separate phase with its own relative velocity

# Turbulent poly-dispersed channel flow

## Turbophoresis effects



## Kinetic and PDF equations

- Smoluchowski coagulation equation
- Population balance equation (PBE)
- Boltzmann equation (BE)
- Method of Moments
- Generalized population balance equation (GPBE)

## Quadrature-based moment methods

- Numerical Methods and Closure problem
- Gaussian quadrature
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- EQMOM
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## Applications

- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
- Porous media
- UQ and other applications

- ▶ Slip velocity (based on the review of Manninen et al., 1996) solved with Newton-Raphson method
- ▶ Drag and lift forces
- ▶ Tomiyama relations (Tomiyama et al., 2002) for drag and lift coefficients

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

$$C_L = \begin{cases} \min[0.288 \tanh(0.121 \text{Re}); 0.00105 Eo^3 - 0.0159 Eo^2 - 0.0204 Eo + 0.474]; & Eo < 4 \\ 0.00105 Eo^3 - 0.0159 Eo^2 - 0.0204 Eo + 0.474; & 4 < Eo < 10 \\ -0.27 & \text{elsewhere} \end{cases}$$

- ▶ Lift and drag coefficients depends on Eotvos number (in our case mainly bubble diameter)
- ▶ Lift changes sign at about 5.8 mm (for the test case under study)

Another force has been considered close to the wall (**wall-lift force**) based on the models of Tomiyama et al. (1995), Hosokawa et al. (2002), Antal et al. (1991) (see also review of Rzehak et al., 2012)

Turbulence model must be included (either DNS, LES or RANS)

- ▶ PBE models are usually expressed only in terms of time-averaged RANS formulation
- ▶ Turbulent dispersion force added as isotropic turbulent diffusivity in the DQMOM equations
- ▶ Coalescence kernel (Laakkonen, 2007; Prince and Blanch, 1990; Coulaloglou and Tavarides 1977):

$$\alpha(\lambda, L) = C_A \epsilon^{1/3} (\lambda + L)^2 (\lambda^{2/3} + L^{2/3})^{1/2} \left( -6 \cdot 10^9 \frac{\mu_l \rho_l \epsilon}{\sigma^2} \left( \frac{\lambda L}{\lambda + L} \right)^4 \right)$$

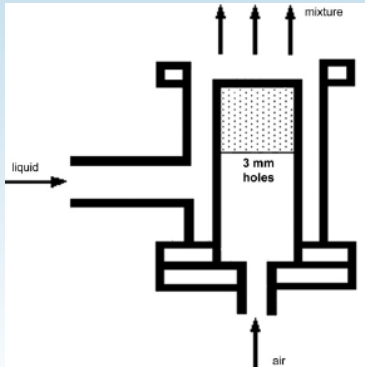
- ▶ Breakup kernel (Laakkonen, 2007; Alopaus et al., 2002):

$$\beta(L) = C_B \epsilon^{1/3} \operatorname{erfc} \left( \sqrt{0.04 \frac{\sigma}{\rho_l \epsilon^{2/3} L^{5/3}} + 0.01 \frac{\mu_l}{\sqrt{\rho_l \rho_g} \epsilon^{1/3} L^{4/3}}} \right)$$

- ▶  $\beta$ —PDF Daughter distribution function (binary)
- ▶ constants taken from Laakkonen, 2007 and Buffo et al., 2011

# Gas-liquid vertical pipe

## Test case description



### Test Case 1:

- ▶ Gas superficial velocity 0.05 [m/s]
- ▶ Water superficial velocity 0.25 [m/s]

### Test Case 2:

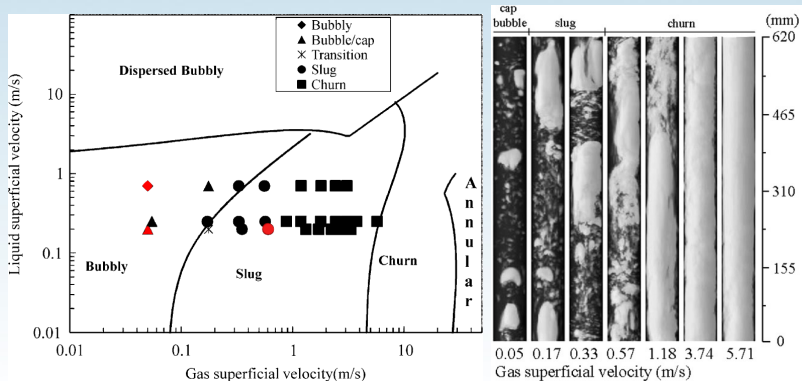
- ▶ Gas superficial velocity 0.05 [m/s]
  - ▶ Water superficial velocity 0.7 [m/s]
- mean void fraction known from experiments

- ▶ experimental data (Szalinsky et. al., 2008)
- ▶ height 6.0 [m]
- ▶ diameter 0.067 [m]

Results analyzed in terms of void fraction profiles at the outlet and bubble size

# Flow regimes

Figure taken from Szalinsky et al. (2010)



2 test cases (red points) of bubbly flow with moderate gas fraction ( $<0.1$ ) and Stokes number ( $<10$ )

## INLET BSD

- ▶ The bubbles enter the pipe through 3mm diameter holes
- ▶ the model of Miyahara et al. (1983) and Nicholas et al. (1991) has been used to estimate the initial bubble size distribution, based on the system and the sparger properties
- ▶ a log-normal distribution has been used with a mean diameter of 7 mm
- ▶ inlet lognormal parameters, mean and STD, can have strong influence on the overall results

The "Classic ASM" model (without population balance) instead has a fixed bubble size derived with a fitting procedure



- ▶ RANS standard  $k - \epsilon$  model for mixture phase
- ▶ Coarse grid :  $307 \times 15$
- ▶ Fine grid:  $620 \times 33$
- ▶ Steady state 2D axisymmetric domain
- ▶ Convection: HPLA scheme

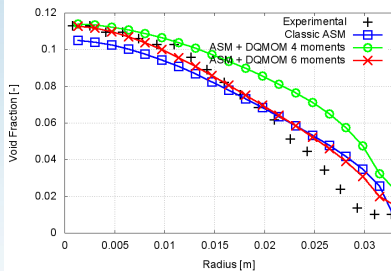
## MODEL VALIDATION

- ▶ Mesh
- ▶ Pipe height (3 m vs 6 m)
- ▶ steady VS unsteady formulations

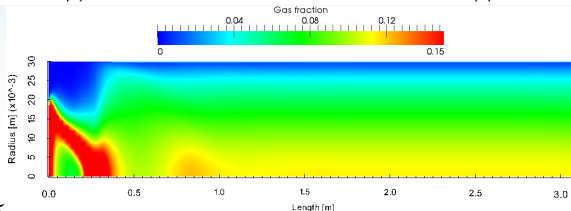
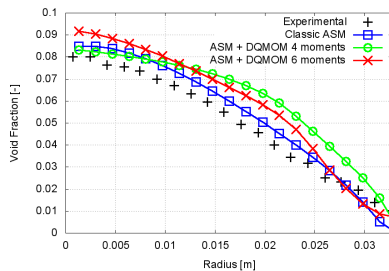
## RESULTS

- ▶ Experimental profile
- ▶ Classic ASM
- ▶ ASM + DQMOM 4 moments
- ▶ ASM + DQMOM 6 moments

$V_L = 0.25$



$V_L = 0.7$

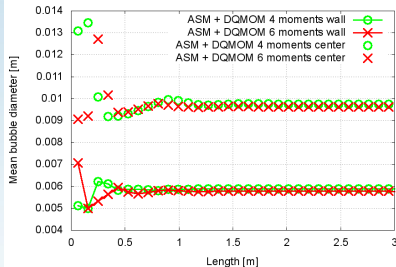


$V = 0.25$

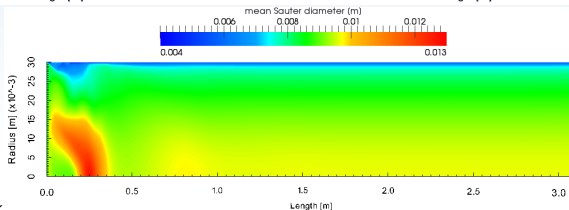
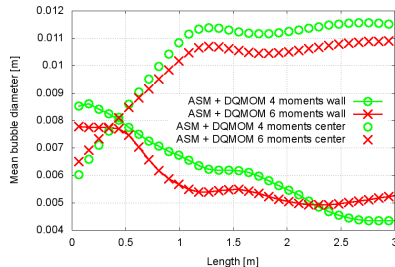
# Vertical pipe flow

Results - Sauter diameter - at wall and in the center

$V_L = 0.25$



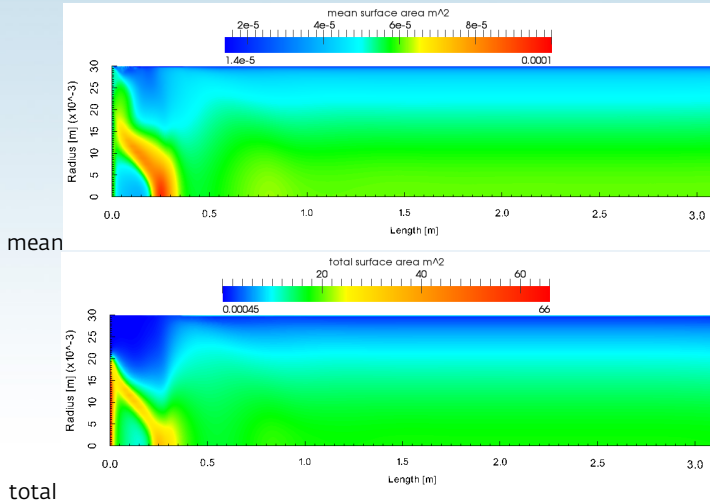
$V_L = 0.7$



$V = 0.25$

# Vertical pipe flow $V_L = 0.25$

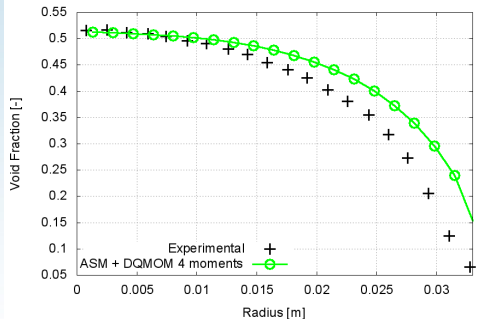
Results - Bubble surface area



# Vertical pipe flow $V_G = 0.57$

## Slug flow test

A test for slug flow regime has also been tested



Surprisingly this model gives good results for void fraction but BSD is no more coherent because it cannot include slugs formation

## Kinetic and PDF equations

- Smoluchowski coagulation equation
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- Boltzmann equation (BE)
- Method of Moments
- Generalized population balance equation (GPBE)

## Quadrature-based moment methods

- Numerical Methods and Closure problem
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## Applications

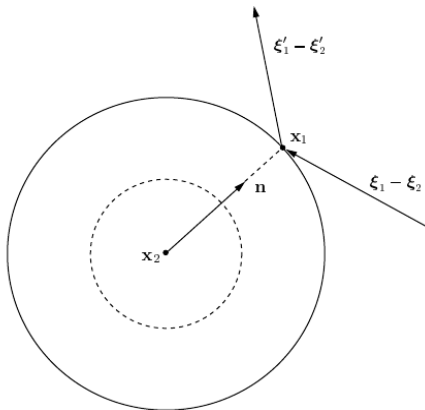
- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
- Porous media
- UQ and other applications

# Boltzmann equation

Homogeneous isotropic case (HIBE)

Particle Velocity Distribution

$$f(U_p; x, t) = \int_{\mathcal{R}} f(L, U_p; x, t) dL$$



## MODEL EQUATION

- ▶ scalar molecular speed  $\xi$
- ▶ distribution of velocities  $f(\xi)$
- ▶ no spatial derivatives
- ▶ only collisions  $\mathcal{Q}(f, f)$
- ▶ Hard-sphere model
- ▶  $x = \cos(\angle_1 \angle n)$ ,  $y = \sin(\angle_2 \angle n)$
- ▶ collision frequency  $|\xi_2 y - \xi_1 x|$

HIBE evolution equation:  $\frac{df}{dt} = Q(f, f)$

$$Q = 2\pi^2 a^2 \int_0^{+\infty} \xi_2^2 \int_{-1}^{+1} \int_{-1}^{+1} (f(\xi_1')f(\xi_2') - f(\xi_1)f(\xi_2)) |\xi_2 y - \xi_1 x| dx dy d\xi_2$$

Let us introduce the even moments  $M_{2p} = \Phi_p$  (density  $\Phi_0$ , energy  $\Phi_1$ , etc.).

After change of variable  $E = \frac{\xi^2}{2}$  and a few manipulations:

$$\frac{d\Phi_p}{dt} = 4\pi\sqrt{2} \int_0^\infty Q(f, f) E^{p+1/2} dE =$$

$$16\pi^3\sqrt{2} \int_0^\infty \int_0^\infty \int_{-1}^{+1} \int_{-1}^{+1} |q| [(C_p^+) - (C_p^-)] f(E)f(E_*)(EE_*)^{1/2} dx dy dE_* dE$$

$$q = yE_*^{1/2} - xE^{1/2}, \quad C_p^+ = [E(1 - x^2) + E_*y^2]^p, \quad C_p^- = E^p$$



## COLLISIONAL INTEGRAL

$$\int_0^\infty \int_0^\infty \int_{-1}^{+1} \int_{-1}^{+1} |q| [(C_p^+) - (C_p^-)] f(E) f(E_*) (EE_*)^{1/2} dx dy dE_* dE$$

$$\sum_{i=0}^{M/2} \sum_{j=0}^{M/2} \int_{-1}^{+1} \int_{-1}^{+1} |q| [(C_p^+) - (C_p^-)] w_i w_j dx dy dE_* dE$$

Written in terms of pre-collisional quantities only  $\rightarrow$  quadrature approximation

$$\tilde{f}(E) \approx \sum_{i=1}^{M/2} \frac{w_i}{4\pi\sqrt{2E}} \delta(E - E_i) \quad \Rightarrow \quad \frac{d\Phi_p}{dt} \approx \frac{\pi}{\sqrt{2}} \sum_{i=1}^{M/2} \sum_{j=1}^{M/2} w_i w_j \Lambda_{ij,p}$$

at equilibrium  $Q = 0 \rightarrow \frac{d\Phi_p}{dt} = 0$  **BUT** this is not guaranteed with the quadrature approximation

Collisions drive the flows towards the wrong steady state

$$\frac{d\Phi_p}{dt} = \frac{\pi}{\sqrt{2}} \sum_{i=1}^{M/2} \sum_{j=1}^{M/2} w_i w_j \Lambda_{ij,p} = S_p$$

$w_i$  and  $E_i$  calculated from  $\Phi_p$  with inversion algorithms<sup>7</sup>

- ▶ QMOM fails to approach the equilibrium → source term must be corrected
- ▶ **Static correction** (QMOM+SC):

$$\frac{d\Phi_p}{dt} = S_p - S_p^{eq}$$

- ▶ **Dynamic correction** (QMOM+DC) weighted with a distance from equilibrium:

$$\frac{d\Phi_p}{dt} = S_p - \left| \frac{\Phi_p(t) - \Phi_p(0)}{\Phi_p^{eq}(t) - \Phi_p(0)} \right|^h S_p^{eq}, \quad h = 1.5$$

---

<sup>7</sup>Product-Difference or Wheeler algorithms

Let us consider a closed box of particles far from equilibrium (initial velocity distribution NOT Gaussian):

**QMOM** approximation selecting  $M$  moments  
( $M/2$  nodes and weights)

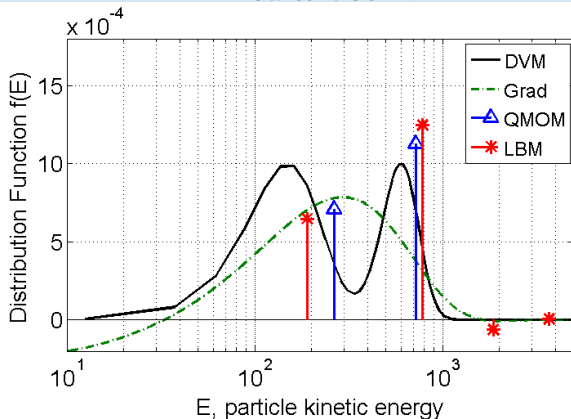
## COMPARISON WITH:

- ▶ **Discrete Velocities Method (DVM)**: reference results with 400 discrete velocities - HomIsBoltz open-source Matlab code (Asinari, 2010)
- ▶ **Grad expansion method (GM)** of order  $M$  with generalized Laguerre polynomials
- ▶ Quadrature approximation with  $M$  fixed Laguerre nodes  $\rightarrow$  **Lattice Boltzmann Method (LBM)** with off-lattice prescribed velocities

# QMOM approximation vs DVM, Grad, oLBM

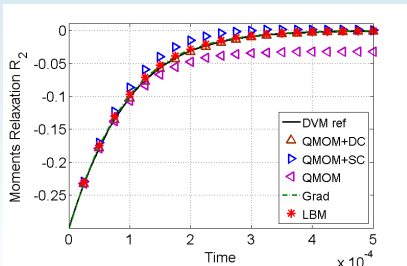
Homogeneous Isotropic Boltzmann Equation (HIBE)

$M = 4$   
Initial condition

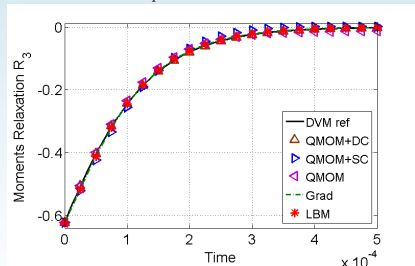


$$M = 4$$

$$\text{Relaxation to equilibrium } R_p = \frac{\Phi_p - \Phi_p^{eq}}{\Phi_p^{eq}}$$



2nd energy moment

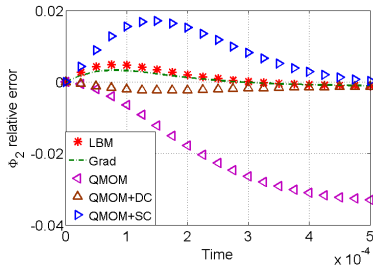


3rd energy moment

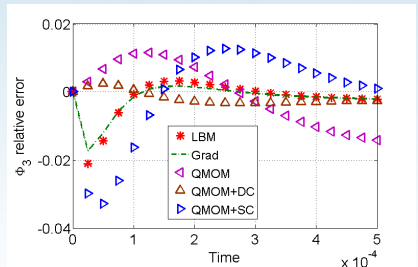
# QMOM approximation vs DVM, Grad, oLBM <sup>3</sup>

Homogeneous Isotropic Boltzmann Equation (HIBE)

$M = 4$   
Relative error on  $\Phi_p$



2nd energy moment



3rd energy moment

## Comparison of steady-state moments

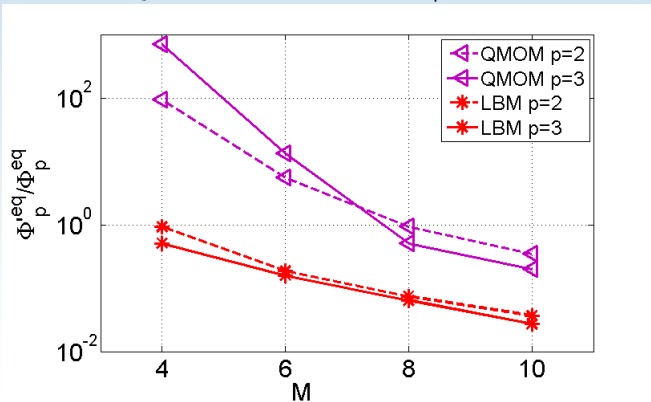
$M = 4$

$M = 6$

$M = 8$

$\times 10^8$	$\Phi_2$	%	$\Phi_2$	%	$\Phi_2$	%
Grad (exact)	1.0034	0.0	1.0034	0.0	1.0034	0.0
oLBM	1.0033	0.01	1.0034	0.003	1.0034	0.001
QMOM	0.9704	3.29	0.9979	0.55	1.0022	0.12
QMOM+SC/DC	1.0034	0.0	1.0034	0.0	1.0034	0.0
$\times 10^{11}$	$\Phi_3$	%	$\Phi_3$	%	$\Phi_3$	%
Grad (exact)	1.4921	0.0	1.4921	0.0	1.4921	0.0
oLBM	1.4919	0.02	1.4921	0.004	1.4921	0.002
QMOM	1.4707	1.44	1.4874	0.31	1.4910	0.08
QMOM+SC/DC	1.4921	0.0	1.4921	0.0	1.4921	0.0
$\times 10^{14}$			$\Phi_4$	%	$\Phi_4$	%
Grad (exact)	-	-	2.8529	0.0	2.8529	0.0
oLBM	-	-	2.8527	0.005	2.8528	0.002
QMOM	-	-	2.8302	0.80	2.8478	0.18
QMOM+SC/DC	-	-	2.8529	0.0	2.8529	0.0
$\times 10^{17}$			$\Phi_5$	%	$\Phi_5$	%
Grad (exact)	-	-	6.6666	0.0	6.6666	0.0
oLBM	-	-	6.6662	0.006	6.6665	0.002
QMOM	-	-	6.6244	6.34	6.6548	0.18
QMOM+SC/DC	-	-	6.6666	0.0	6.6666	0.0

Quadrature error at the true equilibrium





## Kinetic and PDF equations

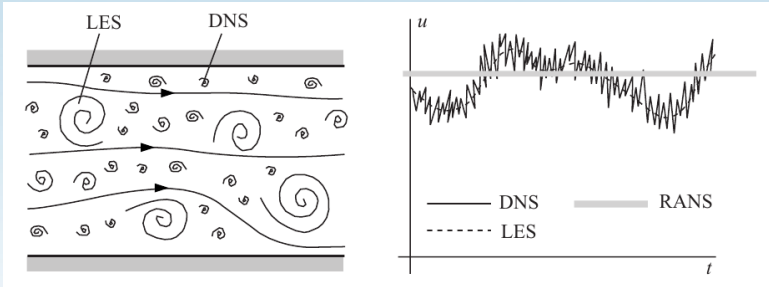
- Smoluchowski coagulation equation
- Population balance equation (PBE)
- Boltzmann equation (BE)
- Method of Moments
- Generalized population balance equation (GPBE)

## Quadrature-based moment methods

- Numerical Methods and Closure problem
- Gaussian quadrature
- QMOM and DQMOM
- EQMOM
- Multivariate case
- Implementation in CFD codes / spatial inhomogeneity

## Applications

- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
- Porous media
- UQ and other applications



## DIRECT NUMERICAL SIMULATION (DNS)

All the flow-scales are solved without model  $\Rightarrow$  virtual experiments (3D and unsteady)

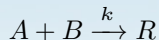
## LARGE EDDY SIMULATION (LES)

Equations are filtered in space (or frequency). Bigger 3D unsteady scales are solved; smaller ones are modelled with **sub-grid scale (SGS) models**

## RANS

Time-averaged equations  $\Rightarrow$  only the mean flow is predicted

- ▶  $N_s$  species denoted by capital letters  $A, B, C, \dots, R, S$
- ▶ Vector of concentrations  $\phi = (\phi_1, \dots, \phi_{N_s})$
- ▶ Consider a simple reaction



- ▶ Transport equations for concentrations with source terms

$$S_A = -k\phi_A\phi_B = S_B$$

- ▶ In turbulent flows a RANS average (in time) or LES filter (in space) is performed

$$\langle S_A \rangle = -k\langle \phi_A \phi_B \rangle \neq -k\langle \phi_A \rangle \langle \phi_B \rangle$$

- ▶ In general the term  $\langle S(\phi) \rangle \neq S(\langle \phi \rangle)$

- The chemical source term can be closed if we assume the existence of a joint probability density function of the concentrations

$$\langle S(\phi) \rangle = \int S(\psi) P(\psi; x, t) d\psi$$

- Rigorously, when using LES we are dealing with a filtered-density function

$$P(\psi; x, t) = \int \delta(\psi - \phi(x, t)) G(r - x) dr$$

where  $G$  is the LES filter

- For the box filter this could be no more a PDF so we simply assume a PDF  $P$  that represents the spatial dishomogeneity in the cells such that

$$\int \psi P(\psi; \mathbf{x}, t) d\psi = \langle \phi \rangle$$

is the filtered scalar and

$$\int (\psi_{\alpha}^2 - \langle \psi_{\alpha} \rangle^2) P(\psi_{\alpha}; \mathbf{x}, t) d\psi_{\alpha} = \langle \phi'_{\alpha}{}^2 \rangle$$

the scalar fluctuation

- $P$  can be solved in a advection-reaction-diffusion equation with  $N_s + 4$  independent variables

**Transport in physical space**

$$\frac{\partial P}{\partial t} + \frac{\partial \langle U_i \rangle P}{\partial x_i} = \frac{\partial}{\partial x_i} \left( D_T \frac{\partial P}{\partial x_i} \right)$$

Time derivative

↓

Convection

Diffusion

**Transport in composition space**

$$- \frac{\partial}{\partial \psi_\alpha} ([\langle D \nabla^2 \phi_\alpha | \psi \rangle + S_\alpha(\psi)] P)$$

Mixing term

↓

Chemical Source term

- The turbulent diffusion term comes from the assumption that the conditional fluctuations  $\langle U'_i | \psi \rangle P = -D_T \frac{\partial P}{\partial x_i}$
- Molecular mixing term needs to be modeled

- The most simple and popular model for Eulerian simulations is the IEM

$$\langle D\nabla^2 \phi_\alpha | \psi \rangle = -\frac{C_\phi}{\tau} (\psi - \langle \phi \rangle)$$

- It is a linear relaxation of the scalars to the mean value with time scale  $\tau$  and a parameter  $C_\phi$
- $\tau$  is chosen to be a turbulence time scale,  $\frac{2k}{\epsilon}$  for RANS and  $\frac{2\Delta^2}{D+D_T}$  where  $\Delta$  is the filter width
- $C_\phi$  is the scalar-to-mechanical time-scale ratio and it depends on the local Schmidt and Reynolds numbers (for gases at high  $Re$   $C_\phi \approx 2$ )

- In the Quadrature Method of Moments (QMOM) the integrals are approximated using a quadrature rule

$$\int g(\psi) P(\psi; x, t) d\psi \approx \sum_{i=1}^M g(\phi_i) w_i$$

where  $\phi_i$  are the abscissas and  $w_i$  the weights of the quadrature rule

- For a given set of  $2M$  moments, the  $M$  abscissas and weights can be calculated using inversion algorithms (Wheeler or Product-Difference)
- This means that we are approximating the exact PDF  $P$  with a multi-environment PDF  $f$

$$f_{\phi}(\psi; x, t) = \sum_{i=1}^M w_i(x, t) \delta[\psi - \phi_i(x, t)]$$

where  $\delta$  is a multi-dimensional delta function



- ▶ In the DQMOM transport equations for  $w_i$  and  $w_i \psi_i$  are solved instead of equations for  $\mu_i$
- ▶  $M(1 + N)$  equations with some constraints (e.g.  $\sum_{i=1}^M w^i = 1$ )
- ▶ The source term is such that the first  $M(1 + N)$  moments are coherent with the transported ones
- ▶ Let us consider a competitive reaction scheme simplified using a mixture fraction  $\xi$  and a reaction progress  $Y$  (linear combination of species concentration). This results in  $N = M = 2$  and  $\phi = (\xi, Y)$

$$\frac{\partial w_1}{\partial t} + \bar{U}_i \frac{\partial w_1}{\partial x_i} - \frac{\partial}{\partial x_i} \left( D_T \frac{\partial w_1}{\partial x_i} \right) = 0, \\ w_2 = 1 - w_1$$

$$\begin{aligned} \frac{\partial w_1 \xi_1}{\partial t} + \bar{U}_i \frac{\partial w_1 \xi_1}{\partial x_i} - \frac{\partial}{\partial x_i} \left( D_T \frac{\partial w_1 \xi_1}{\partial x_i} \right) \\ = \frac{C_\phi}{\tau} w_1 w_2 [\xi_2 - \xi_1] + \frac{D_T}{\xi_1 - \xi_2} \left( w_1 \frac{\partial \xi_1}{\partial x_i} \frac{\partial \xi_1}{\partial x_i} + w_2 \frac{\partial \xi_2}{\partial x_i} \frac{\partial \xi_2}{\partial x_i} \right), \end{aligned}$$

$$\begin{aligned} \frac{\partial w_2 \xi_2}{\partial t} + \bar{U}_i \frac{\partial w_2 \xi_2}{\partial x_i} - \frac{\partial}{\partial x_i} \left( D_T \frac{\partial w_2 \xi_2}{\partial x_i} \right) \\ = \frac{C_\phi}{\tau} w_1 w_2 [\xi_1 - \xi_2] + \frac{D_T}{\xi_2 - \xi_1} \left( w_1 \frac{\partial \xi_1}{\partial x_i} \frac{\partial \xi_1}{\partial x_i} + w_2 \frac{\partial \xi_2}{\partial x_i} \frac{\partial \xi_2}{\partial x_i} \right), \end{aligned}$$

$$\begin{aligned}
\frac{\partial w_1 Y_1}{\partial t} + \bar{U}_i \frac{\partial w_1 Y_1}{\partial x_i} - \frac{\partial}{\partial x_i} \left( D_T \frac{\partial w_1 Y_1}{\partial x_i} \right) \\
= w_1 S(\xi_1, Y_1) + \frac{C\phi}{\tau} w_1 w_2 [Y_2 - Y_1] \\
+ \frac{D_T}{Y_1 - Y_2} \left( w_1 \frac{\partial Y_1}{\partial x_i} \frac{\partial Y_1}{\partial x_i} + w_2 \frac{\partial Y_2}{\partial x_i} \frac{\partial Y_2}{\partial x_i} \right),
\end{aligned}$$

$$\begin{aligned}
\frac{\partial w_1 Y_2}{\partial t} + \bar{U}_i \frac{\partial w_1 Y_2}{\partial x_i} - \frac{\partial}{\partial x_i} \left( D_T \frac{\partial w_1 Y_2}{\partial x_i} \right) \\
= w_2 S(\xi_2, Y_2) + \frac{C\phi}{\tau} w_1 w_2 [Y_1 - Y_2] \\
+ \frac{D_T}{Y_2 - Y_1} \left( w_1 \frac{\partial Y_1}{\partial x_i} \frac{\partial Y_1}{\partial x_i} + w_2 \frac{\partial Y_2}{\partial x_i} \frac{\partial Y_2}{\partial x_i} \right).
\end{aligned}$$

Only the progress variable  $Y$  has a source term  $S$

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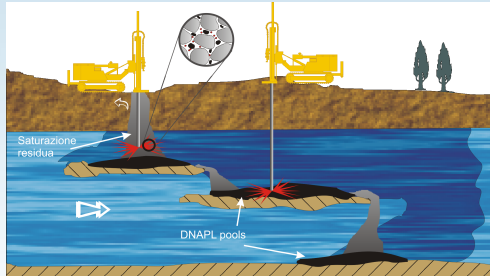
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## Zero-valent iron nano-particle injection



### OBJECTIVES

- ▶ Develop predictive macro-scale transport and reaction models
- ▶ Determine unknown parameters

### CHALLENGES

- ▶ Limited experimental data
- ▶ Multi-scale multi-physics problem

## LENGTH/TIME SCALES

- ▶ **field/reservoir scale:** large spatial variations of material properties and parameters
- ▶ **core/lab scale:** homogenized and averaged equations with constant effective parameters
- ▶ **pore/CFD scale:** fluid continuum equations
- ▶ **molecular/single-pore scale:** molecular discrete models

## PORE SCALE

- ▶ governing equations: Stokes or Navier-Stokes + particle transport (Eulerian or Lagrangian)
- ▶ porous matrix is undeformable and represent domain boundaries
- ▶ micro-scale parameters and fluid properties are considered known and fixed
- ▶ particles can (sometimes) be considered of negligible size

## 1 – PRE-PROCESSING

- ▶ extraction of porous media properties
- ▶ creation of realistic packings
- ▶ fix and modify pore geometry (grain contacts, external container)

## 2 – SETUP AND SIMULATION

- ▶ meshing
- ▶ realistic boundary conditions
- ▶ numerical schemes for NS and ADR

## 3 – POST-PROCESSING

- ▶ mesh convergence analysis, error estimation
- ▶ data analysis and model validation
- ▶ upscaling and estimation of macroscopic parameters

**Problem:** how to get a realistic geometry representative of a generic porous media? Given porosity and grain size distribution, infinite possible realizations exist

## REAL SAMPLES

- ▶ Images (microCT)
- ▶ Detailed representation of the pore spaces
- ▶ Segmentation and reconstruction of a surface mesh not trivial
- ▶ Process is hardly automatised and result is not "unique"

### PACKING ALGORITHMS:

ballistic sedimentation → DEM, rigid body

dynamic/collective rearrangement → MD, random placing

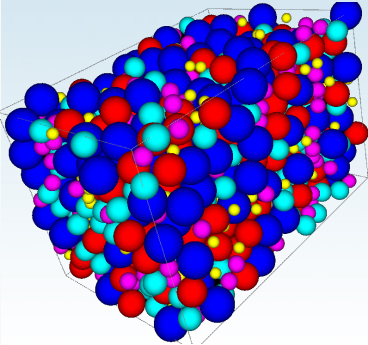
## ALGORITHMIC RECONSTRUCTION

- ▶ From simple models to (quasi)-realistic porous media
- ▶ Easier to build different test cases and compute statistics
- ▶ No need of expensive instrumentation
- ▶ Choice of parameters not trivial



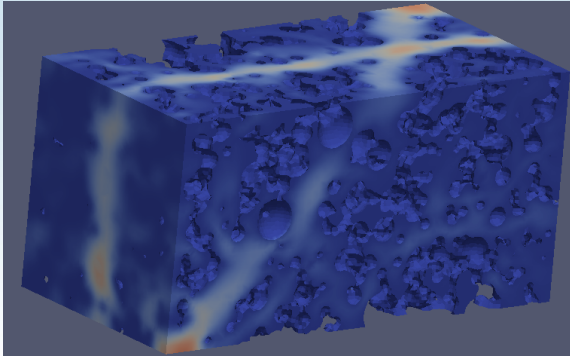


Bullet physics (Blender)



MD-like (A. Donev)

Nice YouTube animations: "Porous medium packing (blender visualization)"

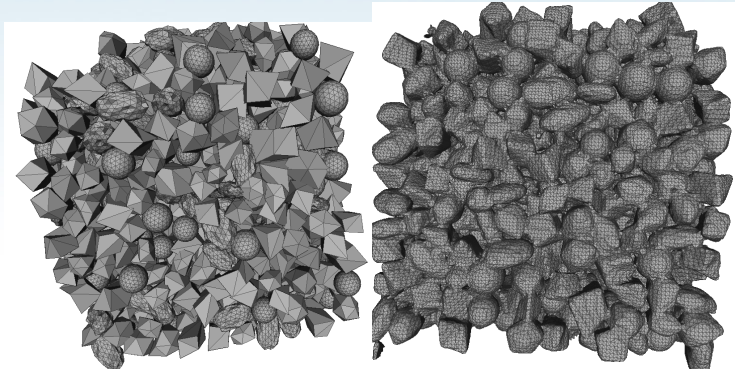


- ▶ Fully random independent placement from distribution  $f(x, y, z)$
- ▶ Post-processing with Jodrey-Tory algorithm to reduce overlapping
- ▶ Randomization of the surfaces

### SURFACE TRIANGULAR MESH (E.G., STL)

- ▶ Porosity: must be calculated a posteriori
- ▶ Contacts: if the packing algorithm is not exact there can be overlapping or non-touching grains
- ▶ Non-realistic features: too sharp or smooth edges

Mesh resampling with Marching Cubes algorithms



**Assumptions:** Newtonian fluids, undeformable porous media, isothermal, ...

## MICRO-SCALE MODELS

$u$  velocity

$p$  pressure

$C$  concentration/ volume fraction/  
phase-field

$D_0$  molecular diffusion

## MACRO/MESO-SCALE MODELS

$V$  Darcy flux

$P$  pressure

$C$  concentration/ saturation/  
phase-field

$K$  permeability

$D$  dispersivity

$$\partial_x p = -\frac{\mu}{K} V$$

Darcy's law

$$\partial_x P = -\frac{\mu}{K} V - \rho \beta V^2$$

Darcy-Forchheimer

$$\partial_x P = -\frac{\mu}{K} V - \mu_{eff} \Delta V$$

Brinkman

$$\rho \partial_t V + \partial_x P = -\frac{\mu}{K} V$$

Unsteady Darcy

...

Two miscible incompressible fluids,  $\rho_1 \approx \rho_2$ ,  $\mu_1 \approx \mu_2$ , one-way coupling.

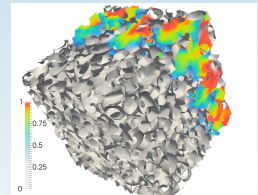
## PORE-SCALE MODEL

Steady Navier Stokes equations in the pore space,  
 $\mu = \mu_1$ ,  $\rho = \rho_1$

$$\nabla \cdot u = 0 \quad u \cdot \nabla u = -\frac{1}{\rho} \nabla p + \frac{\mu}{\rho} \Delta u$$

Advection Diffusion Reaction:

$$\frac{\partial c}{\partial t} + \nabla \cdot (uc + D_0 \nabla c) = r$$



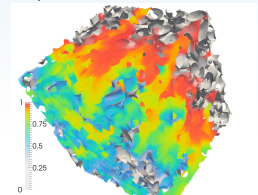
Pore-scale simulation of solute transport (Icardi et. al, Phys. Rev. E, 2014)

## DARCY-SCALE MODEL

$$\nabla \cdot v = 0 \quad v = -\frac{K}{\mu} \nabla P$$

Advection-Dispersion-Reaction:

$$\frac{\partial C\phi}{\partial t} + \nabla \cdot (vC + D\phi \nabla C) = R$$



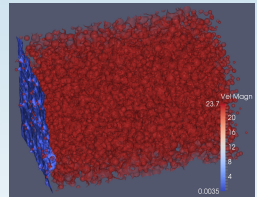
## PORE-SCALE MODEL:

$$\frac{\partial}{\partial t}\rho + \nabla \cdot (\rho u) = 0$$

$$\rho \frac{\partial}{\partial t}(u) + \rho u \cdot \nabla(u) = -\nabla p + \mu \Delta u + \nabla \cdot (\tau_m) + \kappa \sigma n \delta(\Gamma)$$

Advection Diffusion Reaction (unsteady):

$$\frac{\partial c}{\partial t} + \nabla \cdot (uc) = r$$



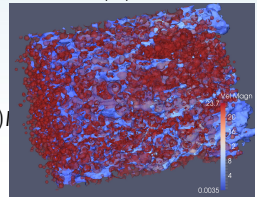
Pore-scale simulation of CO<sub>2</sub> injection  
(Icardi et. al, in preparation)

## DARCY-SCALE MODEL (MIXTURE)

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho v) = 0 \quad v = -\frac{\kappa}{\mu} (\nabla P - \rho \frac{\partial v}{\partial t}) \quad \kappa = K_r(C)$$

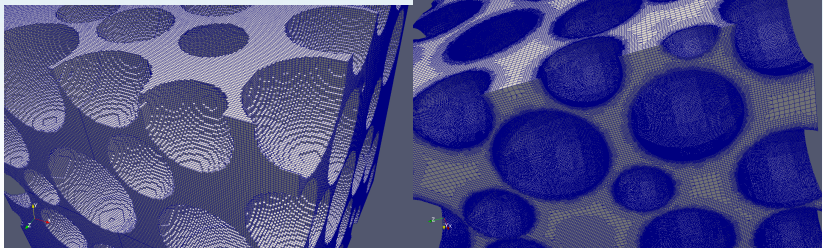
Advection-Dispersion-Reaction (saturation equation):

$$\frac{\partial C \phi}{\partial t} + \nabla \cdot (v_c C + D \phi \nabla C) = R$$



### IMMERSED BOUNDARIES VS BODY-FITTED GRIDS

- ▶ IB are accurate but not adaptable and first order near the wall
- ▶ BF are fully adaptable but difficult to build high quality elements
- ▶ Octree refinement with adaptation on the surface (cut-cell)



To estimate macro-scale parameter, we have to choose the simplest possible scenario: **Quasi-1D flow**

### FLOW BOUNDARY CONDITIONS

- ▶ Total pressure (or periodic BC with uniform body force) imposed at the inlet/outlet
- ▶ Symmetry (no normal flow) or periodic on the lateral boundaries (infinite medium)
- ▶ Wall conditions to simulate experimental columns (confined medium)

### SCALAR BOUNDARY CONDITIONS

- ▶ Constant Dirichlet (=1) on inlet (or mixed Danckwerts condition)
- ▶ Homogeneous Neumann on outlet and on the grains
- ▶ Ad-hoc mixed BCs on the grain could be derived from micro-scale deposition models

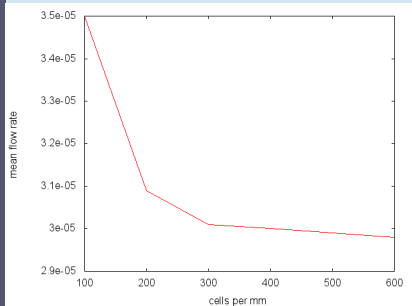
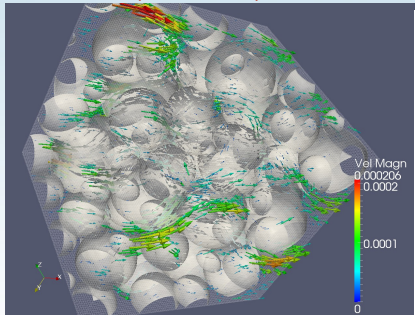
$$\partial_n C = \frac{(1 - \eta(C))}{\eta(C)}$$



# 3D tests – Convergence study with IB

Random spheres packing; porosity 0.6; 600k–80M cells;  $\frac{\Delta P}{\Delta x} = 6 \cdot 10^{-5}$

Sphere packing, 100 grains, high porosity  
Tolerance on permeability set to 3%

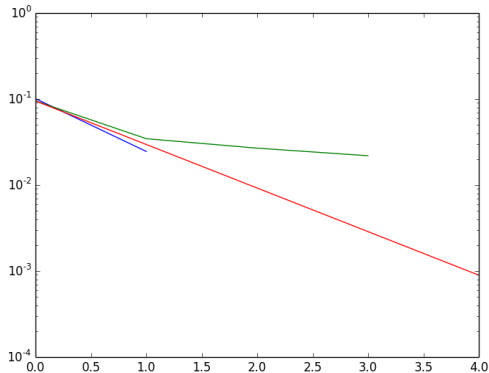


Convergence with standard Immersed Boundary (IB) is not satisfactory (more finite size effects), adapted meshes converge faster

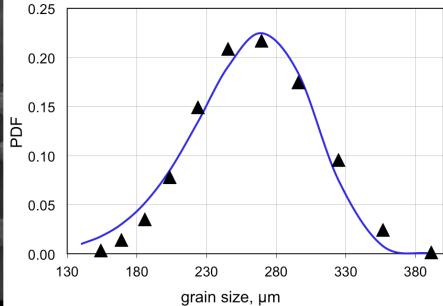
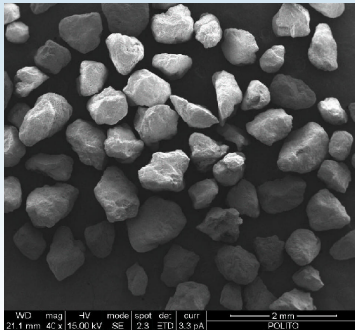
This is confirmed by convergence studies on BCC regular periodic sphere packing

# 3D tests – Convergence study with adapted mesh

Relative error VS refinement level  
uniform refinement (blue), 1:1 refinement (green), 1:2 refinement (red)



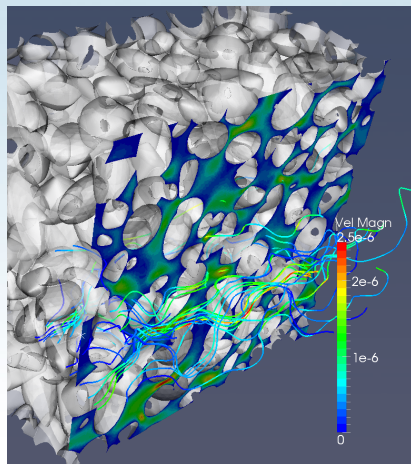
Convergence with adapted mesh faster if the refinement is done correctly

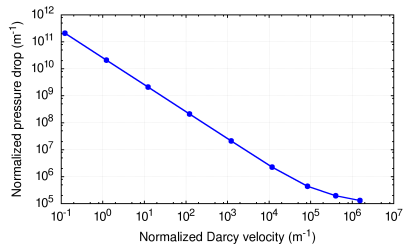
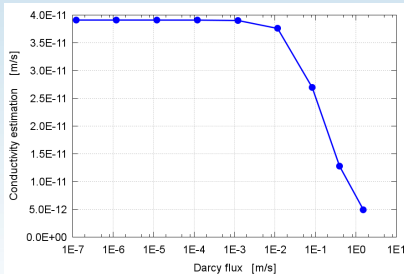


# 3D results – Realistic geometries

*Irregular packing; porosity 0.35; >2000 grains*

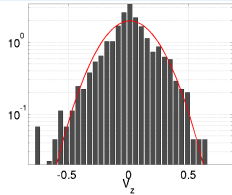
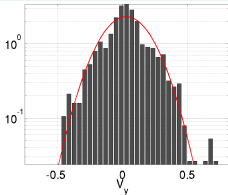
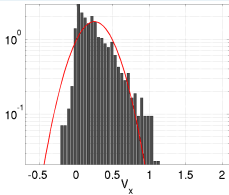
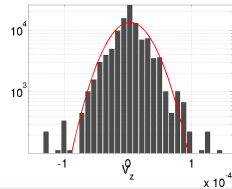
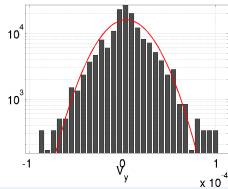
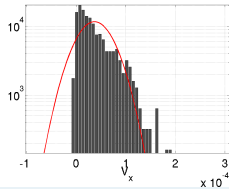
- ▶ OpenFOAM (SnappyHexMesh + SimpleFoam)
- ▶ ScalarTransportFoam + new solvers for steady perfect sink deposition and polydispersed particles
- ▶  $4 \cdot 10^7$  cells
- ▶  $R = 0$
- ▶  $\frac{\Delta P}{\Delta x} = 10^{-5} - 10^2$
- ▶  $Re = 10^{-5} - 10^2$
- ▶  $D = 10^{-9} - 10^{-12}$
- ▶  $Pe = 10^{-2} - 10^6$

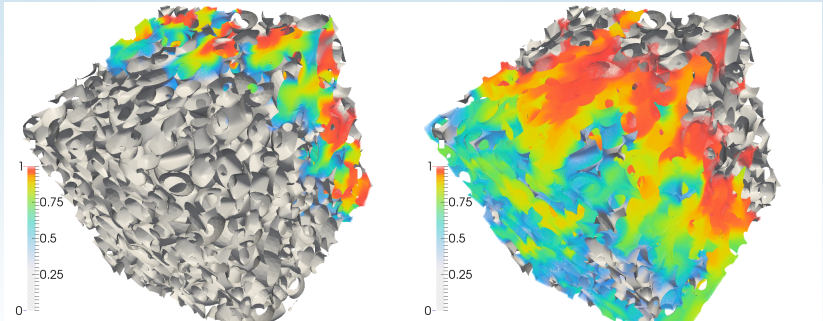




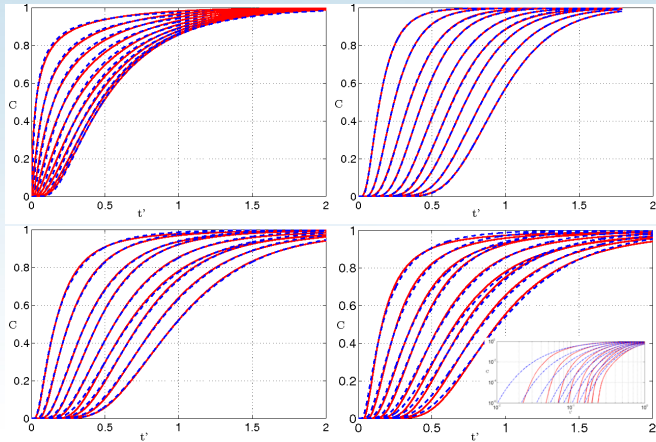
Tortuosity is estimated as  $\frac{\int |u| dV}{\int U_x dV}$

Lagrangian tracers are also computed as post-processing





# Breakthrough curves and parameter estimation



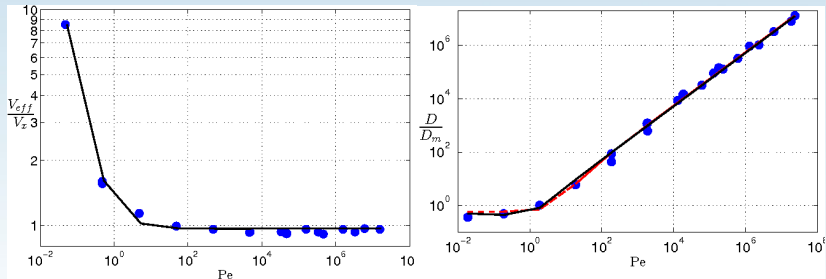


$$\frac{\partial C\phi}{\partial t} + \nabla \cdot (vC + D\phi \nabla C) = 0$$

- ▶ "brute-force" approach: non-linear least-square regression to find the best fitting
- ▶ for more complex models, Bayesian techniques can be used assuming a data misfit model
- ▶ in this work the upscaling can be computed in an explicit form using the **method of moments**

$$V_{eff} = \left( \frac{\epsilon L_x}{M_1} \right), \quad D = \frac{M_2}{2L_x} \left( \frac{V}{\epsilon} \right)^3.$$

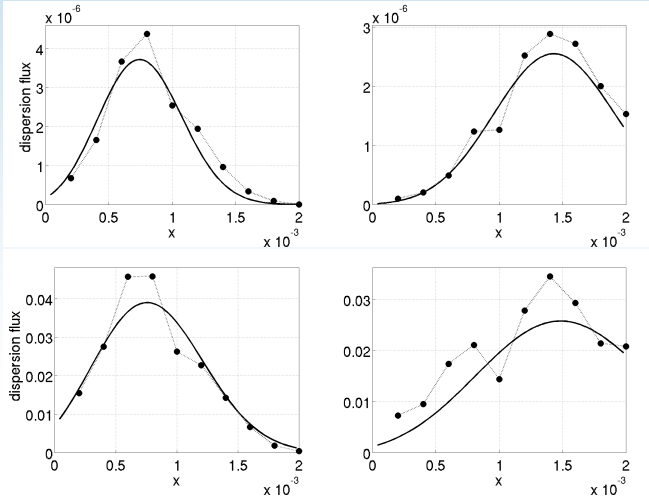
This is equivalent to the computation of the mean square displacement of Lagrangian tracers



Left: effective transport velocity.

Right: Hydrodynamical dispersion. Computational results vs. Van Milligen and Bons, and Bear correlations

$$\langle v'_x c' \rangle \approx -D_L \frac{\partial C}{\partial x}.$$



## Kinetic and PDF equations

- Smoluchowski coagulation equation
- Population balance equation (PBE)
- Boltzmann equation (BE)
- Method of Moments
- Generalized population balance equation (GPBE)

## Quadrature-based moment methods

- Numerical Methods and Closure problem
- Gaussian quadrature
- QMOM and DQMOM
- EQMOM
- Multivariate case
- Implementation in CFD codes / spatial inhomogeneity

## Applications

- Poly-dispersed flows / coupling with turbulence and multiphase models
- Gas-liquid flows
- Non-equilibrium and granular flows / non-smooth kernels
- Turbulent reactive flows / PDF as modelling tool
- Porous media
- UQ and other applications

The idea of QBMM is, in some sense, similar to the approach of arbitrary Polynomial Chaos Expansion (aPC, Oladyshkin and Nowak, 2012)

- ▶ Input random variables  $\xi_i$  known only by moments
- ▶ Moments induce orthogonal polynomials and quadrature rule
- ▶ Stochastic spectral and collocation approaches for computing the response

$$u(\xi) = \sum_{j=0}^P \alpha_j \psi_j(\xi), \quad \langle u(\xi)^n \rangle = \sum_{j=0}^M w_j u_j^n$$

- ▶ Multidimensional correlated variables treated directly or decomposed with Karhunen-Loeve (or POD/PCA)
- ▶ in 1D, the  $n^{th}$ -moment of a random response  $u \in \mathcal{P}^q$ , for a  $k^{th}$ -order PCE, is exactly computed with

$$M = \max\left(\frac{q+k+1}{2}, \frac{nq+1}{2}\right) \text{ collocation points (samples)}$$

- ▶ Forward propagation of uncertainty from moments of input to moments of response

The main advantage in using only moments is the possibility of adaptively updating the quadrature rules, when the underlying PDF changes in time/space

## NON-LINEAR FOKKER-PLANCK

- ▶ Attar and Vedula, 2008; Otten and Vedula, 2011
- ▶ Stochastic Differential equation

$$\dot{x}_i = h_i(x, t) + g_i(x, t)W_i, \quad W_{i,j} \text{ white noise}$$

- ▶ PDF discretized with DQMOM
- ▶ Applications in stochastic control and plasma physics

## NON-LINEAR FILTERING

- ▶ Xu and Vedula, 2009, 2010
- ▶ Propagation step through Fokker-Planck
- ▶ Bayesian update based on quadrature or on EnKF

Other applications of QBMM Bayesian update?

- + QBMM are **easily implementable** in CFD codes
- + Handle complex physical systems, with moderate number of r.v., even if **correlation is not known**
- + the statistical accuracy is solely determined by the number of moments used (adaptivity) and the regularity of the kernels
- + **specifically designed for evolving PDFs in time and space**. It can be thought as a **dynamic optimal quadrature**
  - High stochastic dimensions (it can become a + if an efficient inversion is found for brute-force approach)
  - Moment realizability in advection problems
  - Moments-to-quadrature (QMOM) or source-term (DQMOM) inversion can be ill-conditioned

A smarter way is to employ the recursive relationship for the orthogonal polynomials:

$$\xi \begin{bmatrix} P_0(\xi) \\ P_1(\xi) \\ \vdots \\ P_{N-2}(\xi) \\ P_{N-1}(\xi) \end{bmatrix} = \begin{bmatrix} a_0 & 1 & & & \\ b_1 & a_1 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & & 1 & a_{N-1} \end{bmatrix} \begin{bmatrix} P_0(\xi) \\ P_1(\xi) \\ \vdots \\ P_{N-2}(\xi) \\ P_{N-1}(\xi) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ P_N(\xi) \end{bmatrix}. \quad (51)$$

The nodes of the quadrature approximation  $\{\xi_\alpha\}$ , are the eigenvalues of the tridiagonal matrix appearing in the equation.

This matrix is often re-written in terms of an equivalent tridiagonal symmetric matrix!



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

$$J = \begin{bmatrix} a_0 & \sqrt{b_1} & & & & \\ \sqrt{b_1} & a_1 & \sqrt{b_2} & & & \\ & \sqrt{b_2} & a_2 & \sqrt{b_3} & & \\ & & \sqrt{b_3} & a_3 & \ddots & \\ & & & \ddots & \ddots & \ddots \\ & & & & \ddots & a_{N-2} & \sqrt{b_{N-1}} \\ & & & & & \sqrt{b_{N-1}} & a_{N-1} \end{bmatrix} \quad (52)$$

This procedure transforms the ill-conditioned problem of finding the roots of a polynomial into the well-conditioned problem of finding the eigenvalues and eigenvectors of a tridiagonal symmetric matrix.

The  $N$  weights can then be calculated as  $w_\alpha = M_0 \varphi_{\alpha 1}^2$  where  $\varphi_{\alpha 1}$  is the first component of the  $\alpha^{\text{th}}$  eigenvector  $\varphi_\alpha$  of the Jacobi matrix.

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

$$P_{\alpha,\beta} = P_{1,\beta-1}P_{\alpha+1,\beta-2} - P_{1,\beta-2}P_{\alpha+1,\beta-1} \\ \beta \in 3, \dots, 2N+1 \text{ and } \alpha \in 1, \dots, 2N+2-j. \quad (53)$$

2. where the first row of the matrix is:

$$P_{\alpha,1} = \delta_{\alpha 1} \quad \alpha \in 1, \dots, 2N+1, \quad (54)$$

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

$$P_{\alpha,2} = (-1)^{\alpha-1} M_{\alpha-1} \quad \alpha \in 1, \dots, 2N. \quad (55)$$

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

$$\zeta_{\alpha} = \frac{P_{1,\alpha+1}}{P_{1,\alpha}P_{1,\alpha-1}} \quad \alpha \in 2, \dots, 2N. \quad (56)$$

1. The coefficients of the symmetric tridiagonal Jacobi matrix are then obtained from sums and products of  $\zeta_\alpha$ :

$$a_\alpha = \zeta_{2\alpha} + \zeta_{2\alpha-1} \quad \alpha \in 1, \dots, N \quad (57)$$

$$b_\alpha = -\sqrt{\zeta_{2\alpha+1}\zeta_{2\alpha}} \quad \alpha \in 1, \dots, N-1. \quad (58)$$

2. For example for  $N = 2$  the  $P$  matrix is

$$\begin{bmatrix} 1 & M_0 & M_1 & M_0M_2 - (M_1)^2 & M_0(M_3M_1 - (M_2)^2) \\ 0 & -M_1 & -M_2 & -(M_0M_3 - M_2M_1) & \\ 0 & M_2 & M_3 & & \\ 0 & -M_3 & & & \\ 0 & & & & \end{bmatrix}. \quad (59)$$

The convexity of the function  $\mathbb{E}(M_k)$  with respect to  $k$  can be easily verified by building a difference table of  $\mathbb{E}(M_k)$ .

Example: VALID SET; moment of a Gaussian distribution ( $M_0 = 1, M_1 = 5, M_2 = 26, M_3 = 140, M_4 = 778, M_5 = 4450, M_6 = 26140, M_7 = 157400$ )

k	$d_0 = \mathbb{E}(M_k)$	$d_1$	$d_2$	$d_3$
0	0	1.609	0.039	-0.0043
1	1.609	1.648	0.034	-0.0033
2	3.258	1.683	0.031	-0.0027
3	4.941	1.715	0.028	-0.0022
4	6.656	1.743	0.026	-0.0019
5	8.400	1.770	0.024	0
6	10.171	1.795	0	0
7	11.966	0	0	0

The convexity of the function  $\mathbb{E}(M_k)$  with respect to  $k$  can be easily verified by building a difference table of  $\mathbb{E}(M_k)$ .

Example: **INVALID SET**; moment of a Gaussian distribution ( $M_0 = 1, M_1 = 5, M_2 = 25, M_3 = 140, M_4 = 778, M_5 = 4450, M_6 = 26140, M_7 = 157400$ )

k	$d_0 = \mathbb{E}(M_k)$	$d_1$	$d_2$	$d_3$
0	0	1.609	0	0.113
1	1.609	1.609	0.113	-0.121
2	3.218	1.722	-0.007	0.036
3	4.941	1.715	0.028	-0.002
4	6.656	1.743	0.026	-0.001
5	8.400	1.770	0.024	0
6	10.171	1.795	0	0
7	11.966	0	0	0

- ▶ When using **first-order upwind** spatial discretization schemes and **first-order explicit** time discretization schemes the validity of the moment set should be preserved
- ▶ In all the other cases it is very easy to CORRUPT the moment set and it is anyway safe to have algorithms that **DETECT CORRUPTION AND CORRECT** invalid moment set
- ▶ If we transform the moment set so that  $d_2$  is positive, we are almost sure that the moment set is valid
- ▶ But how positive?
- ▶ The moments of a log-normal distribution have the smallest  $d_3$

$$n(\xi) = \frac{N_T}{\sigma\sqrt{2\pi\xi}} \exp\left(-\frac{(\ln(\xi) - \mu)^2}{2\sigma^2}\right), \quad (60)$$

$$M_k = N_T \exp\left(k\mu + \frac{k^2\sigma^2}{2}\right), \quad (61)$$

- ▶ The log-normal distribution is the smoothest distribution!

## CORRECTION ALGORITHM BY MCGRAW

1. Build the difference table and check if  $d_2$  is negative
2. Identify the moment order  $k$  that causes the biggest change in  $d_3$
3. Change the moment (by multiplying it for a constant) in order to MINIMIZE  $d_3$
4. Go back to point 1

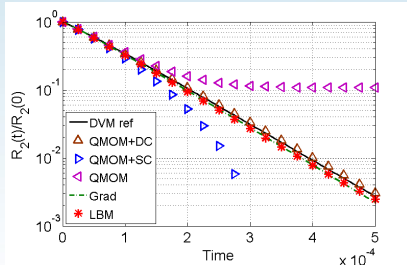
## CORRECTION ALGORITHM BY WRIGHT

1. Build the difference table and check if  $d_2$  is negative
2. Replace the moments with those of a log-normal distribution with

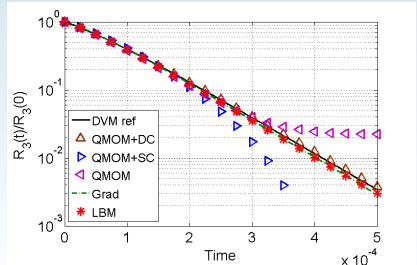
$$\mu = \frac{j}{ij - i^2} \left( \frac{M_i}{M_0} \right) + \frac{i}{ij - j^2} \left( \frac{M_j}{M_0} \right) \quad (62)$$

$$\sigma^2 = \frac{1}{1 - i/j} \left[ \frac{2}{j^2} \left( \frac{M_j}{M_0} \right) - \frac{2}{ij} \left( \frac{M_i}{M_0} \right) \right] \quad (63)$$

$M = 4$   
Normalized relaxation rate



2nd energy moment

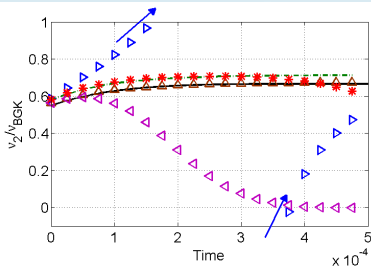


3rd energy moment

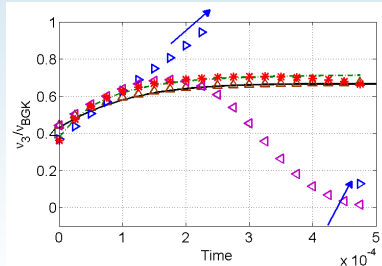


$$M = 4$$

$$\text{BGK-equivalent relaxation time } \nu_p(t) = \frac{d\Phi_p}{dt} \frac{1}{\Phi_p^{eq} - \Phi_p}$$



2nd energy moment



3rd energy moment

$$\frac{d\Phi_p}{dt} = \frac{\pi}{\sqrt{2}} \left( \sum_{i=1}^{M/2} \sum_{j=1}^{M/2} w_i w_j \Lambda_{ij,p}^+ - \sum_{i=1}^{M/2} \sum_{j=1}^{M/2} w_i w_j \Lambda_{ij,p}^- \right)$$

$$\delta_{ij} = \sqrt{E_j/E_i}; \quad q_{ij} = q(x, y, E_i, E_j); \quad C_{ij,p}^+ = C_p^+(x, y, E_i, E_j);$$

$$C_{i,p}^- = C_p^-(E_i); \quad \Lambda_{ij,p}^+ = \int_{-1}^{+1} \int_{-1}^{+1} |q_{ij}| C_{ij,p}^+ dx dy; \quad \Lambda_{ij,p}^- = \int_{-1}^{+1} \int_{-1}^{+1} |q_{ij}| C_{i,p}^- dx dy$$

$$\Lambda_{ij,p}^+ = 2E_i^p \sqrt{E_+} \sum_{\alpha=0}^p \binom{p}{\alpha} \sum_{\beta=0}^{p-\alpha} \binom{p-\alpha}{\beta} (-1)^{\gamma_{ij}} E_i^{-\beta-\alpha} E_+^\alpha E_-^\beta \left[ \frac{2}{2\beta+1} \left( \frac{1-r_{ij}^{2\alpha+2}}{2\alpha+2} + \frac{r_{ij}^{2\alpha+2}}{2\alpha+2\beta+3} \right) + \frac{1}{\beta+1} \left( \frac{r_{ij}^{2\alpha+2}}{2\alpha+1} - \frac{r_{ij}^{2\alpha+2}}{2\alpha+2\beta+3} \right) \right]$$

$$\Lambda_{ij,p}^- = 2E_i^p \sqrt{E_+} \left( 1 + \frac{r_{ij}^2}{3} \right)$$

$$\gamma_{ij} = \begin{cases} \alpha & \text{if } E_i \geq E_j \\ \beta & \text{if } E_i < E_j \end{cases} \quad E_+ = \max(E_i, E_j); \quad E_- = \min(E_i, E_j); \quad r_{ij} =$$

$$\sqrt{\frac{E_i}{E_j}}, \sqrt{\frac{E_j}{E_i}}$$