几个自主开发的气固两相流封闭模型推荐

——气固两相流封闭模型使用总结

Coypyrights 来自上海交通大学 Pelab 研究组

Independent Development of Gas-Solid Closure Models Used in Industrial Reactors

——Summary of applicability of gas-solid closure models

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Note: The research outcomes below come from the Pelab Group in Shanghai Jiao Tong University and the copyrights of the outcomes reserve to the Pelab Group. The data set, UDF, and open-source Python code that support the findings of our study are available from the corresponding author upon reasonable academic request. If you have any academic questions, please feel free to reach out to group leader Prof. Luo (luozh@sjtu.edu.cn).

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0. Introduction

0. 前言

上海交通大学化学化工学院Pelab研究组开展了**流态化反应器内气固两相流介尺度建模及机器学习**的研究工作，自主发展了几类介尺度修正模型，包括材料性质依赖的亚格子曳力模型（较适用于**快速气固稀相流**）、梯度依赖的亚格子曳力模型（较适用于**鼓泡/湍动气固密相流**）、亚格子滤波曳力模型（较适用于**快速气固稀相流**及**部分气固密相流**）等。有感于气固两相流系统的复杂特性，现将所发展出的几类介尺度模型与同行交流分享。这几类模型经包括本组在内的多个国际同行课题组测试后，结果表明：在开展粗网格两相流模拟仿真时，可明显改进预测效果，初步验证了其有效性。希望有更多同行继续开展相关方面的模型开发、评估及测试工作，旨在进一步发展完善两相流模型，推动介尺度理论新研究范式的发展。

需要说明，上述模型是基于Pelab研究组多年来的积淀发展出的，**仅用于学术交流目的**。若需要商业用途请与研究组联系时说明。这些模型仍存在一些不足之处，有待进一步改进、完善及发展，欢迎各位老师同学拍砖。若有不当之处，敬请老师同学批评指正！点击**蓝色**字体可直接链接到所建立模型的原文出处。

本文中，“基准曳力”或“均匀曳力”特指未修正的曳力系数。“有效曳力系数”或“滤波曳力系数”特指修正的曳力系数。

In this manuscript, the term "standard drag" or "uniform drag" refers to the uncorrected drag coefficient. The term "effective drag " or "filtered drag" refers to the modified drag coefficient.

Note: Clicking the blue words can directly link to the original article of the model. The research outcomes below are only used for academic purposes!

1. A gradient-dependent three-marker sub-grid drag correction model

1. 梯度依赖的三标记亚格子曳力修正模型

A parabolic distribution closer to the physical reality is proposed to characterize the local inhomogeneity, and the concept of "multi-subdomain concentration gradient" is introduced. The subgrid modeling is performed in a coarse grid, and a gradient-dependent three-marker subgrid drag model is established. The results [1] show that the greater the concentration gradient, the smaller the subgrid drag correction factor and the greater the local nonuniformity. The coarse-grid simulation results [1] under various operating conditions in turbulent fluidized beds show better grid independence (The mesh convergence quality is increased by 3~5 times) and the computational efficiency and accuracy are improved. Compared with the fine grid simulation that the author tested, the computing speed of coarse-grid simulation is expected to increase by more than 40 times [2]. The effective drag coefficient is given by [2]:

提出了更接近物理实际的“抛物线分布”函数，引入了“多子域浓度梯度”概念，用于表征局部非均匀性。在单个粗网格内进行亚格子建模，发展出了梯度依赖的三标记曳力模型。研究结果表明 [1]：浓度梯度越大，亚格子曳力修正因子越小，局部非均匀性越大。多工况下，粗网格模拟湍动流化床的网格无关性较好（网格收敛效果提高 3~5 倍），计算效率与精度得到提升 [1]。针对作者所测试的 case, 与细网格模拟相比，粗网格模拟的计算速度可提高 40 倍以上 [2]。有效曳力系数为 [2]:

$$\beta_{\text{effective}} = H\frac{18\mu_g\varepsilon_g(1-\varepsilon_g)}{d_p^2}F_d(Re,\varepsilon_g) \tag{1}$$

$$H_d = (\varepsilon_g)_{\text{term}}\,\text{Re}_{\text{term}}(\Delta\varepsilon_g)_{\text{term}} \tag{2}$$

$$(\varepsilon_g)_{\text{term}} = 46.429 - 175.44\varepsilon_g + 443.45\varepsilon_g^2 - 769.3\varepsilon_g^3 + 701.24\varepsilon_g^4 - 246.455\varepsilon_g^5 \tag{3}$$

$$Re_{\text{term}} = pow(Re,(-4.0614 + 2.9368\exp(0.47648\varepsilon_g))) \tag{4}$$

$$(\Delta\varepsilon_g)_{\text{term}} = 0.25215 - 0.51151\Delta\varepsilon_g + (0.14801 - 22.488\varepsilon_g^{16.491})(\Delta\varepsilon_g)^2 \tag{5}$$

$$H = \begin{cases}\min(1,H_d) & (\varepsilon_{g,\min} < \varepsilon_g \le 0.97)\\ 1 & (0.97 < \varepsilon_g \le 1 \ \text{ or } \ \varepsilon_g = \varepsilon_{g,\min})\end{cases} \tag{6}$$

$$\Delta\varepsilon_g = \Delta_{grid} \times |\nabla\varepsilon_g| \tag{7}$$

Where the dimensionless drag correlation [3] is expressed by:

其中，无因次曳力关联式为 [3]：

$$F_d(\varepsilon_g,Re) = \frac{10(1-\varepsilon_g)}{\varepsilon_g^2} + \varepsilon_g^2(1+1.5\sqrt{1-\varepsilon_g}) + [0.11(1-\varepsilon_g)(2-\varepsilon_g) - \frac{0.00456}{\varepsilon_g^4} + (0.169\varepsilon_g^2 + \frac{0.0644}{\varepsilon_g^4})(\varepsilon_g\,Re)^{-0.343}](\varepsilon_g\,Re) \tag{8}$$

Note that different uniform drags lead to different subgrid drag corrections. Interested readers may refer to our article [1] for details of a specific derivation process of our subgrid model.

注意到不同的基准曳力可得到不同的亚格子曳力。具体推导过程请参看文章 [1]。

The recommended flow conditions: dense bubbling/turbulent gas-solid flows.

推荐使用的工况：特别适用于**鼓泡/湍动气固密相流**。

2. A material-property-dependent sub-grid drag correction model

2. 材料性质依赖的亚格子曳力修正模型

Based on a concept of "pseudo-steady-state", a material-property-dependent subgrid drag model is constructed [4]. A systematic mesoscale research idea is also proposed [5]. The results [4] reveal that the subgrid drag model is closely related to material properties. Specifically, a larger particle size or density results in a higher subgrid correction factor, and a decrease in gas density or viscosity leads to a decrease in the subgrid drag. Under the two types of representative particle properties, the constructed correction model accords well with the fine-grid simulation data. The results of coarse-grid simulations of five pilot-scale fast fluidization systems present that the developed model has good predictive performance for the systems with different material properties [4]. The effective drag coefficient is given by [4]:

基于“拟稳态”概念构建了流体与颗粒材料性质依赖的亚格子曳力模型 [4]，提出了较为系统的介尺度模型研究思路 [5]。结果表明 [4]，亚格子曳力模型与材料性质密切相关：较大的粒径或密度导致较高的亚格子修正因子，而气体密度或粘度的减小导致亚格子曳力下。在两类代表性的颗粒性质下，所构建的修正模型与细网格模拟数据较为吻合。粗网格模拟 5 套中试尺度快速流态化反应器的结果表明，所开发模型对不同的材料性质体系具有相对较好的预测性能。有效曳力系数为 [4]：

$$\beta_{\text{effective}} = H\beta_{\text{Wen-Yu}} \tag{9}$$

$$H = \begin{cases} \min(1, \max(0.03, H_d)) & (0.03 \le \varepsilon_s < \varepsilon_{s,\max}) \\ 1 & (0 \le \varepsilon_s < 0.03,\ \varepsilon_s = \varepsilon_{s,\max}) \end{cases} \tag{10}$$

$$H_d = \frac{a_{\mu_g} a_{\rho_g} a_{\rho_s}(a_{d_{s,1}}\varepsilon_s^2 + a_{d_{s,2}}\varepsilon_s + a_{d_{s,3}})}{\boldsymbol{u}_{slip}} \tag{11}$$

$$a_{\mu_g} = 1.8477(10^5\mu_g)^{b_0};\ \ b_0 = \left(0.41398\varepsilon_s^2 - 0.5589\varepsilon_s - 0.78198\right) \tag{12}$$

$$a_{\rho_g} = (1+\rho_g)^{b_1};\ \ b_1 = \left(-1.4556\varepsilon_s^3 + 1.8318\varepsilon_s^2 - 0.4921\varepsilon_s - 0.083177\right) \tag{13}$$

$$a_{\rho_s} = 1.6051 \times 10^{-6}\rho_s + 4.3110 \times 10^{-5} \tag{14}$$

$$a_{d_s,1} = -2.5305 + 0.11965 d_s + 0.036723 d_s^2 - 1.2740 \times 10^{-4} d_s^3 + 1.6023 \times 10^{-7} d_s^4 - 6.7841 \times 10^{-11} d_s^5 \tag{15}$$

$$a_{d_s,2} = -1.1103 + 0.047264 d_s - 0.052087 d_s^2 + 1.6366 \times 10^{-4} d_s^3 - 1.9759 \times 10^{-7} d_s^4 + 8.1965 \times 10^{-11} d_s^5 \tag{16}$$

$$a_{d_s,3} = 1.8890 - 0.083996 d_s + 0.018797 d_s^2 - 5.2820 \times 10^{-5} d_s^3 + 6.0709 \times 10^{-8} d_s^4 - 2.4557 \times 10^{-11} d_s^5 \tag{17}$$

$$0.7894 \le \frac{\mu_g}{10^{-5}\mathrm{Pa \cdot s}} \le 10.7894;\ 0.225 \le \frac{\rho_g}{\mathrm{kg \cdot m^{-3}}} \le 30.225 \tag{18}$$

$$50 \le \frac{d_s}{\mu\mathrm{m}} \le 1000;\ 500 \le \rho_s/(\mathrm{kg \cdot m^{-3}}) \le 2500 \tag{19}$$

Where the drag coefficient of Wen and Yu [6] is described below:

其中，基准曳力系数采用 Wen-Yu 模型 [6]，表达式如下：

$$\beta_{\text{Wen-Yu}} = \frac{3}{4}\frac{\varepsilon_s(1-\varepsilon_s)}{d_s}\rho_g C_{D0} \boldsymbol{u}_{slip}(1-\varepsilon_s)^{-2.65} \tag{20}$$

Please refer to our recent article [4] for a specific derivation process.

具体推导过程请参看文章 [4]。

Note: In this model, $\boldsymbol{u}_{slip} = |\mathbf{v}_g - \mathbf{v}_s|$ is the dimensional slip velocity, with a unit of m/s.

注：本模型中$\boldsymbol{u}_{slip}$为有量纲的滑移速度，单位 m/s.

The recommended flow conditions: dilute fast gas-solid flows.

推荐使用的工况：特别适用于**快速气固稀相流**。

3. Conventional and data-driven modeling of filtered model

3. 传统与数据驱动建模的滤波模型

3.1 Conventional filtered model

3.1 传统建模所得到的滤波模型

3.1.1 Filtered drag correction

3.1.1 滤波曳力修正关联式

Unlike most of previous contributions, our work directly introduces the fluid phase gradient as an additional marker [7] to formulate an explicit function correlation for filtered drag correction factor:

与以往大多数研究不同的是，本工作直接将流体相压力梯度作为额外标记变量 [7]，用于封闭滤波曳力，其具体定义如下：

$$\beta_{\text{filter,y}} = H_d \beta \tag{21}$$

$\beta_{\text{filter,y}}$ is the macroscopic drag coefficient for coarse-grid simulations. The specific expression for H_d is given by:

$\beta_{\text{filter,y}}$为粗网格情况下的曳力系数。H_d代数表达式如下 [7]：

$$-\lg(H_d) = A_1 A_2 A_3 + 2.9031\widetilde{u_{slip}^*} + 0.0604(\overline{\nabla P_{g,y}^*}) + 3.0180 \tag{22}$$

$$A_1 = 0.8566 - 0.9967\bar{\varepsilon}_g + 2.1247\bar{\varepsilon}_g^2 - 1.6458\bar{\varepsilon}_g^3 + 0.5742\bar{\varepsilon}_g^4 \tag{23}$$

$$A_2 = -1.6309 - 0.9151\widetilde{u_{slip}^*} - 0.1758(\widetilde{u_{slip}^*})^2 + 0.0200(\widetilde{u_{slip}^*})^3 \tag{24}$$

$$A_3 = 2.2801 - 0.8059(\overline{\nabla P_{g,y}^*}) - 1.7460(\overline{\nabla P_{g,y}^*})^2 - 2.9519(\overline{\nabla P_{g,y}^*})^3 - 2.4812(\overline{\nabla P_{g,y}^*})^4 - 0.7629(\overline{\nabla P_{g,y}^*})^5 \tag{25}$$

$$H_d = \begin{cases} \mathrm{Min}\left(1, \mathrm{Max}(H_d, 0.03)\right) & (0.45 \le \bar{\varepsilon}_g \le 0.97) \\ 1 & \text{Otherwise} \end{cases} \tag{26}$$

β denotes the uniform drag coefficient:

β为均匀曳力系数：

$$\beta = \frac{18\mu_g \bar{\varepsilon}_g (1-\bar{\varepsilon}_g)}{d_s^2} F_d(\widetilde{\mathrm{Re}_s},\ \bar{\varepsilon}_g) \tag{27}$$

Where the asterisk in this section represents a dimensionless form. $F_d(\widetilde{\mathrm{Re}_s},\ \bar{\varepsilon}_g)$ is the dimensionless uniform drag force. '-' and '~' are the average variables, that is, the flow field variables in coarse-grid simulations. Re_s is the particle Reynolds number ($\mathrm{Re}_s=\varepsilon_g\rho_g d_s|\mathbf{v}_g-\mathbf{v}_s|/\mu_g$). To enhance the predictive capability of the uniform drag, Zhu et al. [8] refitted the uniform drag correlation using much more elaborate DNS data under a wide range of operating conditions, expressed by:

其中，*代表无因次变量，$F_d(\mathrm{Re}_s,\ \varepsilon_g)$为无因次曳力。'-'及'~'为平均性质的变量，即粗网格模拟中的流场变量。Re_s 为雷诺数 ($\mathrm{Re}_s = \frac{\varepsilon_g \rho_g d_s|\mathbf{v}_g-\mathbf{v}_s|}{\mu_g}$)。为了强化均匀曳力的预测适用性，作者 [8] 关联了更详细的 DNS 数据，对均匀曳力进行了关联，表达式为：

$$F_d(\mathrm{Re}_s,\ \varepsilon_g) = \frac{10(1-\varepsilon_g)}{\varepsilon_g^2} + \varepsilon_g^2\left(1 + 1.5\sqrt{1-\varepsilon_g}\right) + \begin{bmatrix} 0.0867(1-\varepsilon_g)(2-\varepsilon_g) - \frac{0.1009}{\varepsilon_g^4} + \\ + \left(0.0214\varepsilon_g + \frac{0.1287}{\varepsilon_g^4}\right) Re_s^{-0.0319} \end{bmatrix} Re_s \tag{28}$$

The following quantities are nondimensionalized:

以下变量以无量纲形式呈现：

$$\nabla P_{g,y}^* = \frac{\nabla P_{g,y}}{(\rho_s - \rho_g)g};\ u_{slip}^* = \frac{|u_{slip}|}{v_t};\ \Delta_f^* = \frac{\Delta_f}{(v_t^2/g)} \tag{29}$$

where the terminal velocity in this work is calculated as:

其中，本工作沉降速度计算采用下式:

$$v_t = \frac{g d_s^2(\rho_s - \rho_g)}{18\mu_g} \tag{30}$$

In addition, it is considered that the components of the drag in either the vertical or lateral direction are equivalent in the current work. Further study on an anisotropic drag correction may be performed by interested readers.

此外，本工作认为各个方向上的曳力修正因子是等价的，即仅考虑各项同性。感兴趣的读者可继续开展可向异性相关方面的研究。

The recommended flow conditions: fast dilute gas-solid flows and partial dense flows.

推荐使用的工况：特别适用于**快速气固稀相流**及**部分密相流**。

3.1.2 Filtered interphase heat transfer correction

3.1.2 滤波相间传热关联式

Unlike most of previous contributions, our work directly introduces the interphase temperature difference as an additional marker [7] to formulate an explicit function correlation for filtered interphase heat transfer correction factor:

与以往大多数工作不同的是，本工作直接将相间传热温差作为额外标记变量 [7]，滤波传热修正因子类似于滤波曳力修正因子的形式：

$$H_{heat} = \frac{\gamma_{\mathrm{filter}}}{\gamma} \tag{31}$$

γ_{filter} is the macroscopic interphase heat transfer coefficient for coarse-grid simulations. The specific expression for H_{heat} is given by:

γ_{filter}为粗网格情况下的滤波相间传热系数。H_{heat}表达式如下 [7]：

$$-\lg(H_{\mathrm{heat}}) = B_1 B_2 - 49.8474 - 2.0372 C_{\Delta\tilde{T}} + 4.0014 (C_{\Delta\tilde{T}})^2;\ \ C_{\Delta T} = -\lg\left(|\Delta\tilde{T}|\right) \tag{32}$$

$$B_1 = 3.1487 - 0.0859 \exp\left(-0.9379 \Delta_f^*\right) \tag{33}$$

$$B_2 = c_0 + c_1 C_{\Delta\tilde{T}} + c_2 (C_{\Delta\tilde{T}})^2 \tag{34}$$

$$c_0 = 13.8797 + 6.0046\bar{\varepsilon}_g - 2.7249\bar{\varepsilon}_g^2 - 0.9128\bar{\varepsilon}_g^3 \tag{35}$$

$$c_1 = 0.5698 + 3.0276\bar{\varepsilon}_g - 5.2381\bar{\varepsilon}_g^2 + 2.4681\bar{\varepsilon}_g^3 \tag{36}$$

$$c_2 = -0.9473 - 1.7784\bar{\varepsilon}_g + 2.3781\bar{\varepsilon}_g^2 - 0.9938\bar{\varepsilon}_g^3 \tag{37}$$

Since most of our filtered thermal data are in the range of $0.001 \le H_{heat} \le 1$ (nearly 100%) and $0.45 \le \bar{\varepsilon}_g \le 0.97$, the correlation is further corrected to:

鉴于本工作大部分滤波数据在$0.001 \le H_{heat} \le 1$及$0.45 \le \bar{\varepsilon}_g \le 0.97$范围内，因此滤波相间传热修正模型进一步限制在:

$$H_{heat} = \begin{cases} \mathrm{Min}\left(1, \mathrm{Max}(H_{heat}, 0.001)\right) & (0.45 \le \bar{\varepsilon}_g \le 0.97) \\ 1 & \mathrm{Otherwise} \end{cases} \tag{38}$$

γ denotes the uniform heat transfer coefficient, expressed by:

γ为均匀相间传热系数 [9]，表达式为：

$$\gamma = \frac{6k_g\varepsilon_g(1-\varepsilon_g)\mathrm{Nu}}{d_s^2} \tag{39}$$

Where Nu is the Nusselt number. To expand the applicable range of Nu, Zhu et al. [9] refitted the Nu correlation utilizing more elaborate DNS data, written by:

其中，Nu 是努塞尔数。为了拓展 Nu 的适用范围，作者采用更详尽的 DNS 数据对 Nu 关联式进行了重新拟合[9]：

$$\mathrm{Nu} = (0.83 + 16.21\varepsilon_g - 14.67\varepsilon_g^2)(1 - 0.01Re_s^{0.2}\mathrm{Pr}_g^{\frac{1}{3}}) + \left(1.50 - 2.60\varepsilon_g + 1.31\varepsilon_g^2\right)Re_s^{0.7}\mathrm{Pr}_g^{\frac{1}{3}} \tag{40}$$

Where $\mathrm{Pr_g}$ denotes the Prandtl number ($\mathrm{Pr_g} = \frac{\mathrm{Cp}_g\mu_g}{k_g}$).

其中，$\mathrm{Pr_g}$ 代表普朗特数（$\mathrm{Pr_g} = \frac{\mathrm{Cp}_g\mu_g}{k_g}$）.

The uniform interphase heat transfer coefficient has been well validated and analyzed [9] whereas the filtered interphase heat transfer model has not been validated by experimental data. Interested readers may perform further test and assessment of our filtered heat transfer model.

上述均匀相间传热系数已得到较为系统的验证分析 [9]，而滤波相间传热模型尚未得到实验验证，感兴趣读者可开展相关测试评估研究。

3.1.3 Filtered reaction rate correction

3.1.3 滤波反应速率修正关联式

At first, we tested the dependence of H_{react} on several possible filtered candidate markers (e.g. $\bar{\varepsilon}_g$, Δ_f^*, u_{slip}^* and $\nabla \mathrm{P}_{g,y}^*$). However, H_{react} is only sensitive to variations in $\bar{\varepsilon}_g$ and Δ_f^* whereas the inclusion of the other markers shows minor improvement in H_{react} predictions.

The H_{react} is then formulated [7]:

作者测试了滤波反应速率修正因子(H_{react})对几种可能的滤波候选标记的依赖性(例如 $\bar{\varepsilon}_g$, Δ_f^*, u_{slip}^*及 $\nabla P_{g,y}^*$)。然而，H_{react}仅对$\bar{\varepsilon}_g$和Δ_f^*的变化较为敏感，而引入其他标记对滤波反应速率预测略有改善。据此，作者关联了滤波反应速率修正因子 [7]：

$$H_{react} = \bar{\varepsilon}_g(a_1 + a_2\bar{\varepsilon}_g + a_3\bar{\varepsilon}_g^2) \tag{41}$$

$$a_1 = 5.5047(\Delta_f^*)^{-0.3316};\ a_2 = -13.4203(\Delta_f^*)^{-0.2826};\ a_3 = 8.7707(\Delta_f^*)^{-0.2454} \tag{42}$$

$$H_{react} = \begin{cases} \mathrm{Min}(1, H_{react}) & (0.45 \le \bar{\varepsilon}_g \le 1) \\ 1 & \mathrm{Otherwise} \end{cases} \tag{43}$$

To consider the influence of mesoscale structures on the reaction rate, a first-order solid-catalyzed reaction that converts species A into species B is considered. For complex reaction systems, further investigations are needed.

上述反应速率修正因子适用于一级固相催化反应，对于复杂反应体系还需要进一步研究探索。

3.2 Data-driven filtered model

3.2 数据驱动的滤波模型

This part applied machine learning to assist data-driven filtered two-fluid model development. The data set used for model training and learning was generated from fine-grid TFM simulations. So far, most of machine learning-aided data-driven models are black-box. That is, an explicit algebraic correlation is not feasible. When the code language used for the machine learning platform is inconsistent with that for the CFD solver, the former can be directly converted to the code language used for the CFD solver. An alternative is to build a data loader to realize the data flow communication between the machine learning platform and CFD solver **[10]**. Our recent work adopted a data loader to communicate the machine learning platform and the CFD solver and its workflow is shown in **[10]**. A detailed description of the specific working process is available in our recent study **[10]**, **[11]**. The data set, trained filtered model, and data loader code that support the findings of this section are available from the corresponding author upon reasonable request.

本部分数据驱动建模工作采用了机器学习方法，对细网格模拟得到的样本数据进行

训练与学习。目前绝大部分机器学习模型为黑箱模型，即无法给出明确的代数关联式，为隐式模型。当机器学习平台语言与 CFD 求解器不一致时，可将机器学习平台语言直接转换为 CFD 求解器所采用的语言；也可建立一个数据加载器（Data loader）实现机器学习平台语言与 CFD 求解器之间的数据交互 [10]。本工作主要采用后一种方法，其工作流程及具体说明可参考作者公开发表的文章 [10]，[11]。在读者合理的要求下，**样本数据、训练得到的滤波模型**及**数据加载器代码**可发邮件从作者处获得。

4. Drag and interphase heat transfer models for large particle systems

4. 较大颗粒体系的曳力及相间传热模型

The "large particle" in this section denotes the Geldart D type particles and the partial Geldart B type particles (A particle diameter larger than 200 μm is suggested). In large-particle system, the inhomogeneous flow phenomena such as clustering seem to be not evident and thereby are usually not considered. Interested readers are welcome to apply our model of this section in their CFD-DEM and TFM simulations of flow and heat transfer.

本部分工作中，较大颗粒指的是"部分 Geldart B 类颗粒（建议大于 200 μm 的颗粒）"及"Geldart D 类颗粒"。在较大颗粒体系中，一般无需考虑颗粒聚团等非均匀介尺度现象。感兴趣读者可以将本部分模型应用于 CFD-DEM 或 TFM 模拟流动与传热中。

4.1 Drag model for large-particle systems

4.1 较大颗粒体系曳力模型

The drag coefficient is expressed by:

曳力系数表达式为：

$$\beta = \frac{18\mu_g \varepsilon_g (1-\varepsilon_g)}{d_s^2} \mathrm{Fd}(\mathrm{Re}_s, \varepsilon_g) \tag{41}$$

As we have stated above, $F_d(\mathrm{Re}_s, \varepsilon_g)$ is the dimensionless drag force. Re_s is the particle Reynolds number ($\mathrm{Re}_s=\varepsilon_g\rho_g d_s|\mathbf{v}_g-\mathbf{v}_s|/\mu_g$). To enhance the predictive capability of the drag, Zhu et al. [8] refitted the drag correlation using elaborate DNS data under a wide range of operating conditions, expressed by:

如前文所述，$F_d(\mathrm{Re}_s, \varepsilon_g)$为无因次曳力，$\mathrm{Re}_s$ 为雷诺数（$\mathrm{Re}_s = \frac{\varepsilon_g\rho_g d_s|\mathbf{v}_g-\mathbf{v}_s|}{\mu_g}$）。为了强化

曳力的预测适用性，作者 [8] 关联了更详细的 DNS 数据，对无因次曳力进行了关联：

$$F_{d,micro}(\mathrm{Re}_s, \varepsilon_g) = \frac{10(1-\varepsilon_g)}{\varepsilon_g^2} + \varepsilon_g^2\left(1 + 1.5\sqrt{1-\varepsilon_g}\right) + \begin{bmatrix} 0.0867(1-\varepsilon_g)(2-\varepsilon_g) - \frac{0.1009}{\varepsilon_g^4} + \\ + \left(0.0214\varepsilon_g + \frac{0.1287}{\varepsilon_g^4}\right) Re_s^{-0.0319} \end{bmatrix} Re_s \quad (42)$$

4.2 Interphase heat transfer model for large-particle systems

4.2 较大颗粒体系相间传热关联式

The interphase heat transfer coefficient is expressed by:

相间传热系数 (γ)表达式为：

$$\gamma = \frac{6k_g\varepsilon_g(1-\varepsilon_g)\mathrm{Nu}}{d_s^2} \quad (43)$$

As we have mentioned above, Nu is the Nusselt number. To expand the applicable range of Nu, Zhu et al. [9] refitted the Nu correlation utilizing elaborate DNS data, written by:

如前文所述，Nu 是努塞尔数。为了拓展 Nu 的适用范围，本工作采用更详尽的 DNS 数据对 Nu 关联式进行了重新拟合：

$$\mathrm{Nu} = (0.83 + 16.21\varepsilon_g - 14.67\varepsilon_g^2)(1 - 0.01Re_s^{0.2}\mathrm{Pr}_g^{\frac{1}{3}}) + \left(1.50 - 2.60\varepsilon_g + 1.31\varepsilon_g^2\right)Re_s^{0.7}\mathrm{Pr}_g^{\frac{1}{3}} \quad (44)$$

Where Pr_g denotes the Prandtl number ($\mathrm{Pr_g} = \frac{\mathrm{Cp}_g\mu_g}{k_g}$).

其中，Pr_g 代表普朗特数（$\mathrm{Pr_g} = \frac{\mathrm{Cp}_g\mu_g}{k_g}$）.

The interphase heat transfer coefficient has been well validated and analyzed [9]. Interested readers may perform further test and assessment of our model.

上述相间传热系数已得到较为系统的验证分析 [9]，感兴趣读者可开展相关应用评估研究。

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