

基于物理信息神经网络的两相流动与传热研究进展

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摘要 两相流现象广泛存在于能源化工、航空航天、环境工程等关键工业领域, 其复杂的相间相互作用、界面动力学以及多尺度耦合效应使得数值求解极具挑战性. 传统计算流体动力学方法虽然理论成熟, 但在处理两相流的界面追踪、强非线性、相变传热等核心问题时面临网格依赖性强、计算成本高昂、泛化性较差等技术瓶颈. 物理信息神经网络(physics-informed neural networks, PINN)作为融合深度学习与物理定律的新兴方法, 通过将控制方程、边界条件、实验数据等约束嵌入训练过程, 采用连续函数逼近替代离散网格求解, 有效克服了上述局限性, 为两相流数值求解提供了创新解决方案. 本综述系统梳理了PINN在两相流研究中的理论发展与应用实践, 包括界面追踪方法、多尺度建模策略、自适应权重调整等关键技术, 重点阐述了PINN在气液界面动力学、液液相分离、液固悬流流动、气固颗粒输运以及相变传热等典型两相流系统中的应用进展, 明确了其在相界面追踪、多孔介质渗流、传热传质等关键问题上的有效性. 基于当前研究现状, 本文进一步讨论了PINN方法面临的技术挑战和发展机遇, 为推进两相流智能求解技术的产业化应用提供了重要参考.

关键词 物理信息神经网络, 两相流, 流动, 传热, 机器学习

两相流动与传热现象是现代工业系统中的核心物理过程, 直接影响着关键设备的性能和安全. 在石油开采中, 油气两相流的流动特性决定了采收率的高低^[1]; 核反应堆安全分析需要准确预测沸腾传热的临界热流密度^[2]; 化工反应器内的气液接触效率依赖于对界面传质机制的深入理解^[3]; 航空发动机燃烧室内的液滴雾化与燃烧涉及复杂的气液相变传热^[4]. 这些工程问题均涉及复杂的相间相互作用、界面动力学演化以及跨尺度传热传质过程, 因此对数值建模技术提出了严峻挑战.

传统数值方法在处理两相流问题时面临诸多技术瓶颈. 网格依赖性为首要困难, 复杂几何形状和移动界面使网格生成难度和计算成本呈指数增长^[5]; 其次, 两相流的强非线性特性使得数值求解容易出现收敛困难,

传统方法往往需要采用极小的时间步长以维持数值稳定性^[6]; 再者, 传统的界面追踪算法存在数值扩散和质量不守恒问题^[7]. 对于工程优化和参数研究而言, 传统方法的计算成本更是难以承受^[8], 使得基于数值仿真的设计优化在实际应用中受到严重制约.

物理信息神经网络(physics-informed neural networks, PINN)的兴起为两相流动与传热问题提供了革命性的解决方案^[9,10]. PINN通过将物理定律直接嵌入神经网络损失函数, 实现了数据驱动与物理约束的深度融合^[11]. 相比传统数值方法, PINN具备三大核心优势: 无网格特性避免了复杂几何的网格生成难题, 连续函数表示天然适应界面拓扑变化, 自动微分技术简化了高阶导数计算^[12]. 特别是在处理复杂几何和移动边界问题时, PINN可以避免网格畸变和重构的困难^[13].

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此外, PINN能够从稀疏实验数据中学习潜在的物理规律, 为解决传统数值方法难以处理的逆问题和参数识别问题提供了新的技术途径^[14].

尽管PINN在流体力学^[15~19]和传热学^[20~23]基础研究中显示出巨大潜力, 但其在两相流领域的应用仍处于快速发展阶段. 当前针对两相流复杂物理现象的PINN建模方法缺乏统一的理论指导, 不同两相流问题往往需要专门的网络结构和训练策略, 限制了方法的通用性和可推广性. 此外, 现有文献对PINN在两相流中的计算精度、收敛性能、长期稳定性等关键指标缺乏系统性评估, 影响了方法的工程化应用进程.

基于上述技术背景和发展需求, 本文系统梳理了物理信息神经网络在两相流动与传热领域的最新研究进展. 首先, 介绍PINN的基本原理和针对两相流问题的关键技术改进, 包括界面表征方法、物理约束嵌入策略等核心内容. 随后, 分类总结PINN在气液两相流、液液两相流、液固两相流、气固两相流和相变传热等典型场景中的应用成果. 在此基础上, 深入讨论了当前技术面临的主要挑战, 并展望了未来的发展方向和应用前景. 本综述旨在为两相流数值建模研究者提供全面的技术参考, 推动PINN方法在工程两相流问题中的深度应用和产业化发展.

1 两相流PINN原理

1.1 PINN基础原理

PINN的理论基础源于通用函数逼近定理, 该定理表明神经网络具备逼近任意连续函数的能力, 为偏微分方程的神经网络求解提供了理论保障^[24]. 在此基础上, PINN通过构造包含物理残差的损失函数, 将PDE求解转化为神经网络参数的优化问题. 具体而言, 对于偏微分方程 $F[u(x, t)] = 0$, 网络输出 $u_\theta(x, t)$ 作为真解的近似, 总损失函数由四部分组成并由权重系数 λ 调节各项间的平衡:

$$L = \lambda_{\text{PDE}} L_{\text{PDE}} + \lambda_{\text{data}} L_{\text{data}} + \lambda_{\text{bc}} L_{\text{bc}} + \lambda_{\text{ic}} L_{\text{ic}}, \quad (1)$$

$$L_{\text{PDE}} = \frac{1}{N_{\text{PDE}}} \sum_{i=1}^{N_{\text{PDE}}} \|F[u_\theta(x_i, t_i)]\|^2, \quad (2)$$

$$L_{\text{data}} = \frac{1}{N_{\text{data}}} \sum_{j=1}^{N_{\text{data}}} \|u_\theta(x_j, t_j) - u_j\|^2, \quad (3)$$

$$L_{\text{bc}} = \frac{1}{N_{\text{bc}}} \sum_{k=1}^{N_{\text{bc}}} \|B[u_\theta(x_k, t_k)]\|^2, \quad (4)$$

$$L_{\text{ic}} = \frac{1}{N_{\text{ic}}} \sum_{l=1}^{N_{\text{ic}}} \|u_\theta(x_l, 0) - u_0(x_l)\|^2, \quad (5)$$

其中, 物理损失 L_{PDE} 确保满足物理一致性, 数据损失 L_{data} 用于拟合观测数据, 初始损失 L_{ic} 和边界损失 L_{bc} 保证初始和边界条件的实现; N_{PDE} 、 N_{data} 、 N_{bc} 、 N_{ic} 分别为各类采样点数量; θ 为网络参数; u_j 为观测数据; B 为边界算子.

如图1所示, PINN通过神经网络前向传播、自动微分计算残差、构造损失函数和反向传播优化的循环过程, 实现了物理定律与数据驱动的深度融合. 自动微分机制能够精确计算神经网络输出对输入的各阶偏导数, 有效避免了传统数值微分的截断误差, 保证梯度计算精度^[25]. 在实现技术方面, 采样策略的选择对PINN性能具有重要影响. 配点法通过在计算域内布置采样点来评估物理损失, 随机采样策略则通过每个训练循环中随机选择新采样点提高泛化能力^[26]. 优化算法的选择直接影响收敛性和求解精度, 现有研究中Adam和L-BFGS算法在PINN中使用最为广泛.

1.2 两相流动与传热PINN架构

如图2所示, 两相流PINN关键技术包括物理约束嵌入、损失函数和激活函数优化、网络架构设计、界面表征方法、迁移学习技术等. 两相流PINN与通用PINN最核心的差别在于损失函数中的物理约束项. 两相流动与传热过程的基本控制方程包括连续性方程、Navier-Stokes方程和能量方程, 由于密度 ρ 和黏度 μ 的空间不连续性, 标准梯度计算面临数值困难. 为此, 通常采用人工黏性增强技术^[27,28], 在动量方程中引入稳定项以抑制界面附近的数值振荡. 对于界面物理约束, Young-Laplace方程(式(6))描述界面张力与曲率的平衡关系, 其中表面张力系数 σ 和界面曲率 κ 可通过自动微分精确计算. 相变过程需要额外考虑Stefan条件, 即界面处的热流跳跃条件(式(7)). 由上述方程所构成的物理损失函数中各项量纲通常并不统一, 因此需对各物理项进行权重平衡调整^[29~31].

$$\Delta p = \sigma \kappa, \quad \kappa = \nabla \cdot (\nabla \phi / |\nabla \phi|), \quad (6)$$

$$k_l \frac{\partial T_l}{\partial n} - k_g \frac{\partial T_g}{\partial n} = \rho L v_n, \quad (7)$$

其中, Δp 为界面两侧的压力差, σ 为表面张力系数, κ 为界面的平均曲率, ϕ 为水平集函数, k_l 和 k_g 分别为两相的热导率, T_l 和 T_g 分别为两相的温度, ρ 为所生成新相的密

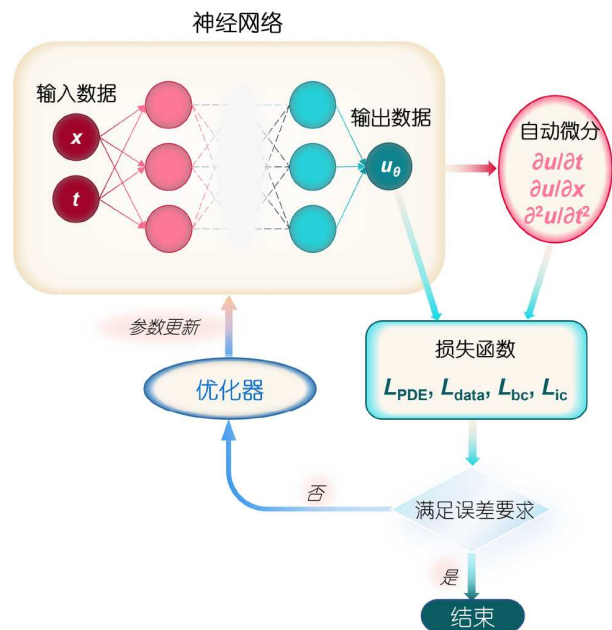


图1 PINN基本训练循环
Figure 1 Basic training cycle of PINN

度, L 为潜热, v_n 为界面法向速度。

如表1所示, 目前两相流PINN的界面表征方法主要包括: (1) VOF方法: 通过体积分数函数 $C(x, t)$ 表征界面, 通常采用 $C = 0.5$ 近似表示界面位置, 该方法天然保证质量守恒^[32~36]; (2) 水平集方法: 采用符号距离函数 $\phi(x, t)$ 描述界面, $\phi=0$ 为界面位置^[36~38]; (3) 相场方法: 采用相场参数 ψ 表征界面, 界面为有限厚度的过渡区域, 通过Cahn-Hilliard或Allen-Cahn方程演化^[36,39]; (4) 神经网络隐函数方法: 直接通过神经网络学习界面几何, 适用于复杂边界条件^[40]。

由于两相流物理场复杂, 现有研究通常通过分支子网络、域分解等手段提高收敛性和计算效率, 各子域网络通过重叠区域的连续性约束保证全局一致性^[41,42]。激活函数对PINN性能有重要影响, 传统tanh函数适合平滑变化区域^[43], 但在界面附近容易出现梯度消失现象。对于复杂两相流问题, 自适应激活函数能够自适应不同区域的物理特征^[44,45], 加入正弦噪声的激活函数适合高梯度流热问题^[46]。

2 PINN在两相流动与传热领域的应用

作为融合物理信息和数据驱动的新兴求解方法, PINN在两相流领域的理论验证与应用研究正处于蓬勃发展时期。下文按两相流常见类型分类, 分别介绍

PINN技术在气液两相流、液液两相流、液固两相流、气固两相流和相变传热领域的研究进展。

2.1 PINN在气液两相流的应用

气液两相流是由气相和液相组成的多相系统。界面张力、浮力、惯性力与黏性力的相互竞争产生了丰富的流动模式, PINN需要准确捕捉气泡的聚并破裂、液滴的分裂融合等动态演化过程^[37,39,41]。气液两相间巨大的密度和黏度差异导致界面区域的数值不稳定性, 传统PINN方法常出现训练困难和预测振荡^[6,35]。

面对这些技术难题, 研究者发展了一系列针对性的PINN框架。对于界面表征方法, Zhou等人^[36]通过系统比较VOF、水平集和相场方法, 证明了VOF在界面捕捉精度方面的显著优势。水平集方法的神经网络化改进则更为显著, Tang等人^[38]将水平集方程直接嵌入PINN损失函数; Silva等人^[37]进一步提出了无重新初始化的水平集-PINN方法, 通过引入光滑映射函数避免了传统水平集方法的重新初始化步骤, 速度重建误差控制在5%以内。神经网络隐函数表征为复杂边界问题提供了新的解决途径, Pan等人^[40]采用神经网络直接表征Young-Laplace界面, 成功处理了非圆形截面毛细管和不连续润湿边界问题, 最大界面误差控制在0.013%以内。物理约束的嵌入策略体现了PINN的核心优势, He等人^[6]提出的人工黏性增强PINN通过在控制方程中引入稳定性项, 将预测误差从80%降至20%以下。自适应权重调整已成为处理多损失项收敛问题的标准技术^[35,36,38], Radhakrishnan等人^[42]基于高斯概率模型的动态权重调整策略在分布式气泡模拟中取得了显著效果。网络架构的优化主要体现在采用并行区域分解方法解决了子域间界面连续性问题^[39,41,42]。

基于这些理论基础, PINN在不同应用领域中展现出了独特优势。对于自由空间气液两相流中的单气泡上升经典问题, Dai等人^[35]通过自适应权重策略成功处理了高密度比条件下的界面不稳定性, 实现了与CFD相当的预测精度还具备处理不适定问题的能力。气泡聚并破裂过程中的拓扑变化现象十分复杂, Qiu等人^[39]采用Cahn-Hilliard方程描述界面演化, 成功模拟了液滴飞溅中的冠状结构形成过程, Sajjad等人^[47]通过PINN预测了池沸腾气泡脱离直径。液滴碰撞融合问题中, Buhendwa等人^[32]基于界面运动数据反演流场信息, 体现了PINN在逆问题求解方面的独特优势。界面不稳定性现象如Rayleigh-Taylor失稳在传统方法中需要高

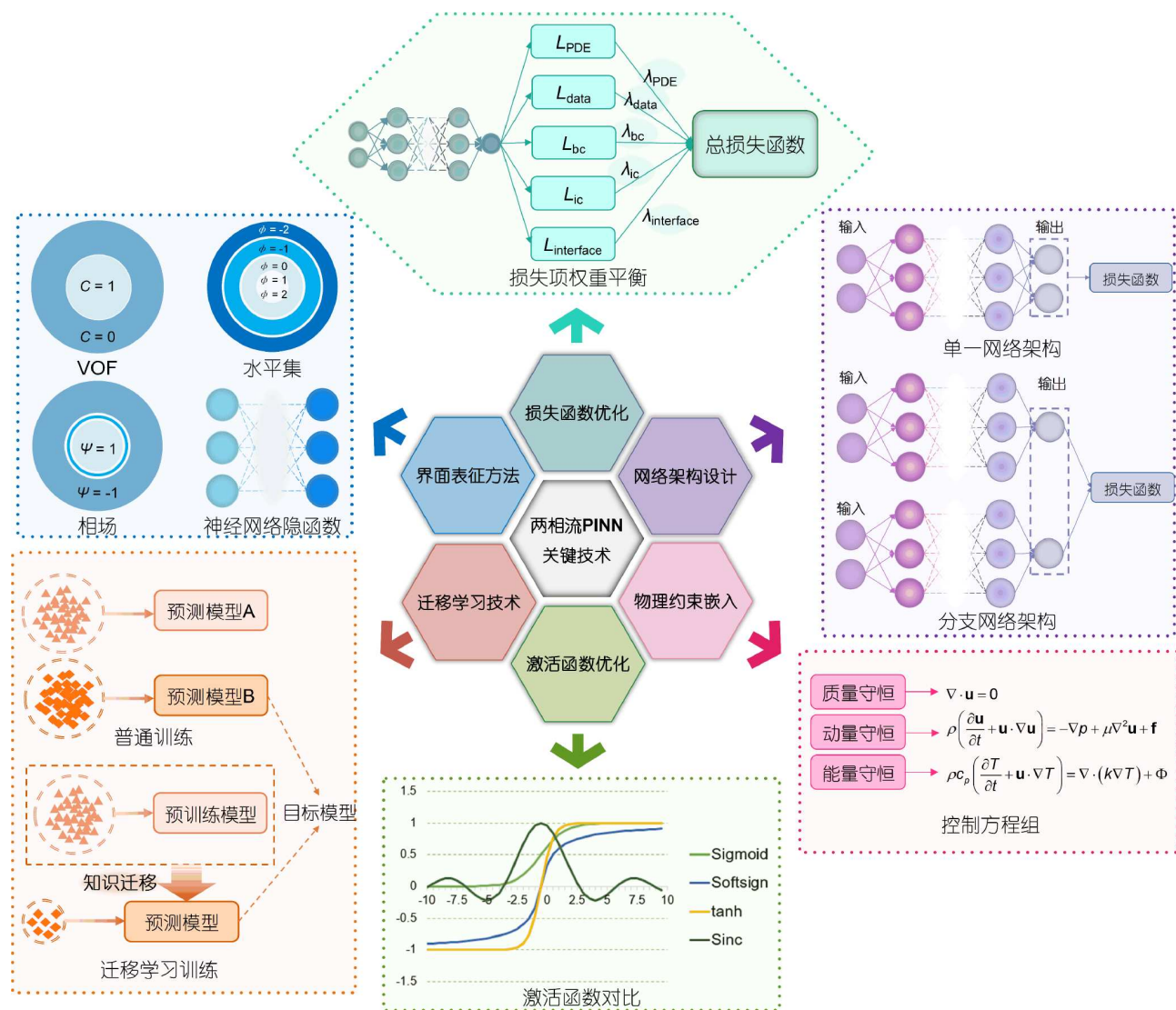


图2 两相流PINN关键技术

Figure 2 Key technologies of two-phase flow PINN

精度网格捕捉, 而PINN的无网格特性为此类问题提供了自然的解决方案^[39,48]. 相对渗透率建模是多孔介质气液流动的关键问题, Patel和Yadav^[49]首次将PINN应用于CO₂混溶黏性指进现象, 通过无网格求解避免了传统方法的网格依赖性, 精度与半解析解高度吻合. Chen等人^[50]开发了针对页岩储层的通用伪组分框架, 将计算速度提升627倍, 预测准确率达到97%. CO₂封存技术是当前的研究热点, Zhang等人^[51]处理的双激波传播问题解决了B-L方程的不连续性挑战, 为CO₂-盐水系统的相间溶解度建模提供了有效工具. 工程复杂气液两相流PINN主要解决多重复杂性的协同处理问题, 例如:

轴承润滑中的空化现象通过硬约束边界处理实现了计算效率300倍的提升^[52]; 地热井筒的复杂几何和热力学平衡约束使得PINN相比传统ANN的MAE降低60%^[53]; 管道系统中的4DVar数据同化技术通过不断比对实测数据和模拟数据, 反向修正模拟初始状态, 将计算时间从小时级缩短至分钟级^[54]; 控压钻井中的环空流动通过自适应权重优化和多阶段时空域划分有效处理了参数剧变区域^[55].

从气液两相流PINN的技术创新角度来看, 界面处理技术从VOF的质量守恒优势^[36]到水平集方法的几何灵活性^[32,37,38], 再到神经网络隐函数的边界适应性^[40],

表 1 两相流PINN界面处理技术

Table 1 Interface processing technologies for two-phase flow PINN

文献	界面表征方法	应用场景	定量性能指标	创新点
Buhendwa等人 ^[32]	VOF	剪切流中的液滴、振荡液滴、上升气泡	MSE: 剪切流液滴0.00122, 振荡液滴0.00115, 上升气泡0.00281	从界面运动求解速度和压力场
Jalili等人 ^[33]	VOF	薄膜沸腾传热	MSE: 体积分数峰值0.35, 温度峰值0.07	首次将PINN应用于薄膜沸腾传热
Yao等人 ^[34]	VOF	微通道气泡生成和合并、流动沸腾	MSE: 单气泡生成0.0028, 双气泡合并0.0064, 流动沸腾0.0398	通过稀疏数据反演未知源项
Dai等人 ^[35]	VOF	气泡上升与破碎	L2相对误差: 压力 1.4180×10^{-3} , 速度 1.3412×10^{-1}	提出自适应加权策略以自动调整损失权重
Silva等人 ^[37]	水平集	气泡上升	速度MSE: $10^{-3} \sim 10^{-2}$ ($t = 1$ s)	提出无需重新初始化的水平集-PINN框架
Tang等人 ^[38]	水平集	蒸汽冷凝液膜生成	液膜厚度误差: 0.005~0.013 mm	将Lee模型嵌入水平集方法, 实现蒸气冷凝快速预测
Zhou等人 ^[36]	VOF、水平集、相场	单气泡上升	平均L2误差: VOF: u 速度5.42%, v 速度5.44%, 压力0.25%; 水平集: u 速度8.36%, v 速度7.00%, 压力0.34%; 相场: u 速度7.46%, v 速度6.05%, 压力0.34%	提出自适应损失权重与时间分治策略, 对比分析了三种界面追踪方法
Qiu等人 ^[39]	相场	气泡上升、液滴飞溅、Rayleigh-Taylor不稳定性	最大相对误差: 13.19%(Rayleigh-Taylor不稳定性)	提出基于重叠区域分解的并行PINN框架, 用于模拟大密度比两相流
Pan等人 ^[40]	隐函数	毛细管上升、接触角识别	接触角预测最大误差: 1.4%	能处理复杂边界和参数识别, 可求解不连续润湿边界

每种方法都在特定应用场景中发挥着不可替代的作用。分布式计算架构的发展为大规模气液两相流问题提供了有力支撑, 从并行重叠区域分解^[39]到分布式PINN^[41,42], 计算效率获得了数倍到数十倍的提升。对于多损失项权重平衡, 从简单的权重调整^[35,36,38]发展到基于物理残差的智能优化^[42], 显著改善了收敛问题。硬约束技术的突破性进展体现了PINN在物理一致性方面的独特优势, 从质量守恒的严格保证^[48]到复杂物理定律的直接嵌入^[33,40,56], 为高精度物理建模奠定了坚实基础。迁移学习技术的引入扩展了PINN的应用边界, 实现了跨工质预测^[57]和跨工况泛化^[33], 为减少训练数据需求和提升模型通用性提供了有效途径。逆问题求解能力的不断增强使得PINN在参数识别、流场重建、设计优化等方面展现出传统方法无法比拟的优势^[32,37,40]。

综上所述, 气液两相流领域的PINN技术已取得显著进展, 在保证预测精度的前提下, 显著提升了计算效率, 并且预测结果符合物理一致性^[48,58], 与传统方法的对比研究更是证实了PINN在处理复杂边界和不适应问题等方面的独特优势^[32,35,40]。然而, 当前技术仍面临一些关键局限性: 界面锐化问题导致的局部误差仍需

进一步改善^[33], 长期稳定性预测能力有待验证, 极端物性比条件下的数值稳定性需要持续优化^[36,41], 距离全面工程化应用仍有发展空间。

2.2 PINN在液液两相流的应用

液液两相流是由2种互不相溶或部分相溶的液体组成的多相流系统, 其相间密度差相对较小、界面张力适中。裂隙多孔介质液液两相流是常见的应用场景, 饱和度前沿的急剧跳跃对数值求解精度要求极高, 传统PINN在强梯度区域往往出现振荡或模糊现象^[59-61], 研究者通常需要引入人工黏性项来稳定计算, 这种做法会改变PDE的原始物理结构^[62-64]。

面对这些建模难题, 研究者发展了一系列针对性的PINN技术方案。针对激波捕捉这一核心问题, Zang等人^[62]提出了Oleinik熵约束方法, 对水含量函数进行分段重构, 消除了函数导数的双值现象, 使PINN在保持方程双曲结构不变的前提下准确捕捉激波位置, 从根本上避免了人工黏性的引入。Yang等人^[65]在此基础上发展了hp-VPINN变分框架, 利用弱残差积分形式自然处理不连续性。网络架构设计方面的创新日趋多样化, Shan等人^[64]首次将LSTM-注意力机制引入PINN,

利用序列记忆能力显著增强了激波捕捉精度, L2相对误差降至0.01972。Lv等人^[66]开发的径向基函数PINN通过显式函数逼近策略简化了训练复杂度, 计算效率较传统卷积PINN提升3倍。为解决非均质介质建模难题, Han等人^[67]设计了十字交叉卷积核, 通过显式表达相邻网格传导率实现了空间不连续性的精确处理, 预测精度 R^2 超过0.99, 工业指标误差控制在2%以内。

石油开采已成为液液两相流PINN技术应用的重点领域。注水开发过程涉及储层尺度的油水渗流和井筒尺度的多相流动, 因此对预测精度和计算效率都提出了很高要求。Zhang等人^[68]、Han等人^[67]和Guo等人^[69]分别建立了基于FVM-PINN和CC-PINN的注采井系统模型, 通过严格的物理约束嵌入实现了压力场和饱和度场的同步高精度预测。Yan等人^[60]通过嵌入式离散裂缝模型与PINN的深度耦合, 成功处理了裂缝-基质界面的复杂相互作用, 训练效率较传统PICNN方法提升10倍。Yan等人^[61]进一步发展了FVM-PICNN框架, 实现了三维复杂裂缝系统中通量连续性的严格保证。在提高采收率技术领域, Liu等人^[70]建立的聚合物驱PINN模型准确预测了增黏剂浓度的时空分布演化, 均方误差达到 10^{-4} 量级, 为聚合物驱方案优化提供了高效工具。

技术创新层面的发展更加注重解决工程实际中的复杂问题。Lin等人^[59]提出的剪枝策略通过冻结同质化预训练参数, 在强非均质储层建模中将训练效率提升3倍, 有效解决了传统方法在极端物性条件下的收敛困难。不确定性量化技术的引入使得PINN预测结果更加可靠, Bootstrap方法被成功用于构建预测置信区间^[65]。Abbasi和Andersen^[71]通过将时间和空间变量替换为与物理特性相关的组合变量, 简化了PINN求解逆流自发渗吸问题的难度, 提高了精度和效率。Zakaria等人^[72]的KED知识增强框架通过虚拟渗透率场生成和半监督学习策略, 为复杂多物理场问题提供了可行的解决路径。

总之, 液液两相流PINN技术在预测精度和计算效率方面较传统数值方法表现出色, 但现有工程研究集中在石油工程领域, 在化工萃取分离、污水处理、海洋工程等其他重要领域的技术验证和推广较为有限。

2.3 PINN在液固两相流的应用

液固两相流系统由连续液相和分散固相组成, 具有固相形状相对固定、颗粒间存在碰撞摩擦以及沉降

特性明显等独特物理特征^[73,74]。在实际工程中, 颗粒的沉降速度、絮凝参数等关键物性受复杂环境条件影响, 传统实验测定方法成本高昂且难以涵盖所有工况, 而基于经验公式的估算又往往精度不足。对此, Delcey等人^[75]提出将沉降速度作为可训练参数直接嵌入PINN损失函数, 通过耦合颗粒和盐度输运方程, 成功识别了复杂环境下颗粒的真实沉降特性。Wu等人^[76]进一步发展了自适应参数化PINN框架, 将传统的固定絮凝参数转化为网络输出并动态优化, 预测精度较传统模型提升88.31%, 为复杂工程环境下的精确建模提供了可能。

液固两相流的长期演化预测对于工程设计和风险评估至关重要, Zhang等人^[77]针对沉降-扩散方程的长时间数值不稳定问题, 创新性地提出了时间归一化PINN策略, 通过引入正弦激活函数和拉丁超立方采样, 使计算精度较传统有限差分方法提升3个数量级。Ohara等人^[78]在河床形态反演中采用质量守恒冗余约束, 仅依靠稀疏的表面流速数据实现了河床高程的无监督识别。这些技术创新表明, PINN在处理液固两相流的长期演化和逆问题求解方面具有传统方法难以企及的优势。

PINN在液固两相流工程应用中已取得显著成果。在石油工程领域, Ehinmowo^[79]将Turian方程作为物理约束用于管道携砂临界速度预测, 有效解决了倾斜管段预测可靠性不足的工程难题。Yan等人^[73]通过修正二阶流体模型描述高浓度水泥浆的颗粒应力, 为固井作业中的流变特性预测提供了高精度工具。水利工程领域的应用更加广泛, 从河道淤积预测^[80,81]到海洋沉积物输运^[77], 再到压力管道沉积建模^[82], PINN均展现出了优异的预测性能。

技术创新方面, PINN在液固两相流领域正朝着智能化和高效化方向发展。Tipu等人^[82]和Wu等人^[76]均采用SHAP方法量化了环境因子对颗粒行为的贡献度, 提升了模型的物理透明度。计算加速技术也不断突破, Ji等人^[74]将颗粒输运方程与流体控制方程同时嵌入损失函数, 构建了双输出网络结构分别预测固液相速度和体积分数, 在水力压裂支撑剂输运预测中节约了98%的计算时间, 为实时预测和过程控制创造了条件。此外, 逆向设计方法的引入使得PINN不仅能够预测液固两相流行为, 还能够优化工程结构参数, Liu等人^[83]利用可微分图神经网络实现了泥石流防控结构的智能设计。

尽管PINN在液固两相流建模中展现出巨大潜力,但仍面临技术挑战和发展机遇。当前方法在处理高浓度非牛顿流体、非球形颗粒复杂几何以及强非线性本构关系方面还存在局限性。

2.4 PINN在气固两相流的应用

气固两相流系统由连续气相和分散固相组成,气固两相的密度比可高达 10^3 倍,这种巨大差异使得耦合方程组呈现强刚性特征,压力泊松方程的求解成为主要计算瓶颈。针对这一难题,Zhang等人^[84]开发的FPM-DEM框架采用UNet架构直接预测流场分布,将连续性方程作为物理约束嵌入损失函数,成功绕过了压力求解的数值困难。Guo等人^[85]进一步构建了质量守恒硬约束模块,通过迁移概率学习确保长期预测的物理一致性,不仅解决了数值刚性问题,还实现了变颗粒数工况的外推预测能力。

气固两相流中颗粒相本构关系的强非线性和不确定性是PINN建模面临的另一关键挑战。由于颗粒相有效黏度同时依赖于浓度和剪切率^[86],因此传统的经验关联式往往无法准确描述复杂工况下的流动行为。对此,Iannello等人^[87]提出的augPINN方法引入了可解释性相间分布参数,实现了气泡相与乳化相对颗粒作用的量化表征。Xu等人^[88]开发了PINN-MPM联合框架,成功解决了燃烧界面演化与颗粒相变化的协同预测问题。颗粒-气体的相互作用机制呈现从单颗粒到颗粒群体行为,再到多物理场耦合的跨尺度特征,Ren等人^[89]的DR-PINN通过解耦表征学习处理生物质气化中的多尺度反应,在保持物理一致性的同时对未知生物质种类的预测精度达到 $R^2 \approx 0.81$,表明PINN在处理气固两相流的跨尺度问题方面具有独特优势。

目前,PINN已在气固两相流的工程应用中取得一系列进展。Xu等人^[88]建立的PINN燃烧模型将预测误差控制在10%以内,计算效率较有限元法提升2个数量级。流化床反应器的工程放大是化工领域的技术难题,Chew和Cocco^[86]将PINN技术引入流化床放大设计,显著缩短了开发周期。催化裂化等石化过程的优化中,深度学习与物理约束的结合使计算效率提升了10倍^[84],为工业过程的实时优化创造了条件。

可以看出,气固两相流PINN技术正处于快速发展阶段,在特定应用场景中已实现显著的计算效率提升和预测精度改善,但复杂几何与极端操作条件下的模型稳定性仍需进一步验证。

2.5 PINN在相变传热的应用

如前文所述,气液、液固等两相流系统中常伴随有相变传热过程,本节着重从热力学角度综述不同两相流领域中PINN处理相变传热问题的方法与应用。相变传热是物质在不同相态间转换时伴随的传热过程,其利用潜热实现高效能量传递的特性,使其在核反应堆安全、增材制造、电子冷却等工程领域具有重要应用价值^[33,90,91]。相变传热建模的核心技术难题是移动边界的精确捕捉和处理,这直接关系到传热预测的准确性和工程设计的可靠性。在传统数值方法中,移动界面的时空演化常导致数值扩散和界面模糊^[34,92]。针对这一关键问题,研究者开发了多种PINN创新框架。Tang等人^[38]提出的水平集-PINN融合方法通过隐式界面描述,计算效率提升4倍,成功处理了竖壁膜状凝结和微重力凝结问题。Jalili等人^[33,57]采用VOF方法结合人工压缩速度技术,有效锐化了气液界面并解决了界面扩散问题。相变潜热的释放或吸收在短时间内会产生巨大的温度梯度变化,使得相变点处潜热的突跃性成为数值求解时不可避免的难题。研究者通过创新的PINN架构设计有效解决了这一问题。Cai等人^[93]和Park等人^[94]采用双网络架构分离界面预测与温度场计算。Hosseini等人^[91]采用的等效热容法和Rouhollahi等人^[95]提出的基于焓的框架,为潜热的隐式处理提供了有效途径,从而避免了显式跟踪相变界面的数值复杂性。此外,相变过程往往伴随复杂的流动、传质和化学反应现象,传统单一物理场建模方法难以准确预测系统行为^[92,96]。面对这一挑战,Yao等人^[34]开发的HFI-PINN框架实现了传热-流动-相变的耦合建模,实现了60%时间外推预测。

在气液相变系统应用中,PINN技术已在沸腾传热领域取得了重要进展。Jalili等人^[33,57]的系列研究中,不仅建立了膜态沸腾的迁移学习框架,研究了过热液体中蒸汽泡的三阶段生长动力学,还实现了水/R-134a/FC-72这3种工质的通用预测,零样本预测误差仅1.3%。微通道沸腾问题中,HFI-PINN框架的计算效率较CFD提升2个数量级^[34]。在蒸发传热方面,Malekjani等人^[97]基于Maxwell理论的液滴蒸发建模证明了无量纲输入可使外推误差降低50%,Jahanbakhsh等人^[98]将Schrage蒸发方程作为硬约束嵌入损失函数,成功实现了薄膜蒸发临界热通量的精确预测。

液固相变系统在材料加工和储能应用中的PINN建模同样取得了突破性进展。Hosseini等人^[91]开发的参数

化PINN求解器在激光加工应用中实现了 10^6 倍的计算效率提升、90%的训练成本缩减。Cai等人^[93]在经典Stefan问题中成功实现了界面位置与热扩散系数的精确反演。Farrag等人^[99]建立了SAC305焊料的固液相分数预测模型,为焊接质量控制提供了理论支撑。相变储能领域的应用中,Priyadarshi等人^[96]对PCM储热系统进行全年动态评估,验证了PINN在储能系统设计中的实用价值。

气固相变PINN建模虽然研究案例相对较少,但在航天和干燥工程等特殊领域展现了技术价值。Mozafari Parsa和Tahsini^[100]所开发的双阶段PINN架构为航空瞬态热防护设计提供了高效分析工具。多孔介质干燥工程中,传统经验模型难以准确描述复杂的传热传质过程,Khan等人^[92]构建的双尺度框架桥接了微观机理与宏观现象,为干燥工艺优化提供了理论基础。

技术创新方面,迁移学习和混合建模已成为相变传热PINN发展的重要方向。由于相变传热问题往往需要处理多种工质、多种工况的复杂组合,传统方法需要针对每种情况重新建模,开发周期长且成本高昂。Jalili等人^[33,57]和Zhao等人^[90]分别实现了跨介质和跨工况的PINN适应框架,进一步提升了相变传热模型通用性。混合建模策略有效结合了物理模型的可解释性与机器学习的自适应能力,研究表明这种方法可以同时提升内插和外推性能,为工程应用提供了更可靠的预测工具^[90,101]。

当前相变传热PINN技术在工程应用中已展现出巨大潜力,在核反应堆、增材制造、工业冷却等关键领域,PINN方法的实时预测能力已达到毫秒级响应^[38,91],为数字孪生和智能控制创造了条件。

3 总结与展望

PINN将神经网络的强大拟合能力与物理约束的先验知识有机结合,具备无网格求解、自动微分、并行计算等独特优势,能够突破传统数值方法在高维复杂

问题上的计算瓶颈,同时避免纯数据驱动方法的物理不一致性问题。本研究深入调研了PINN在两相流领域的技术进展和应用前景,不仅梳理了PINN的核心算法原理以及针对两相流问题的关键改进技术,还系统地总结了五类代表性两相流系统的PINN方法研究进展:气液两相流的界面动力学和流场反演,液液两相流的相分离动力学和多孔介质渗流问题,液固两相流的沉降规律与悬浮稳定性分析,气固两相流的颗粒碰撞与流化特性预测,以及相变传热的传质传热协同效应。这些应用充分验证了PINN在处理两相流复杂物理现象方面的卓越性能。

当前PINN在两相流建模中仍存在若干关键挑战有待攻克:

(1) 方法通用性不足。现有PINN框架缺乏标准化实现方案,不同物理机制和几何条件下的两相流问题往往需要重新设计网络架构和约束策略,未来需发展能够跨问题快速适应的PINN架构。

(2) 界面物理建模精度需要提升。尽管界面处理技术进展显著,但面对极端物性比、强非线性耦合等苛刻条件时仍有改进空间。解决方向包括开发自适应框架提升界面捕捉精度、引入物理感知激活函数等。

(3) 前沿两相流问题探索薄弱。由于PINN受限于偏微分理论模型成熟度,目前研究主要集中于传统两相流系统,对微纳尺度等前沿问题探索相对薄弱,需要针对这些问题发展新的理论框架和计算方法。

(4) 工程化部署能力亟需加强。现有两相流PINN研究多停留在概念验证阶段,存在计算效率和数值稳定性的工业化技术瓶颈,未来应发展轻量化PINN实现实时预测,逐步提升模型可靠性。

综上所述,近年来两相流PINN的应用研究蓬勃发展。随着人工智能与物理学的深度融合,PINN必将在两相流科学研究和工程应用中发挥更加重要的作用,为相关领域的技术创新和产业发展提供强有力的理论工具和技术支撑。

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Summary for “基于物理信息神经网络的两相流动与传热研究进展”

Advances in two-phase flow and heat transfer using physics-informed neural networks

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Two-phase flow phenomena are ubiquitous in critical industrial sectors, including petroleum engineering, nuclear power generation, chemical processing, and environmental applications, where accurate prediction of interfacial dynamics, phase transitions, and heat transfer mechanisms is essential for system safety and operational efficiency. The inherent complexity of two-phase flow systems, characterized by sharp density gradients, moving interfaces, topological changes, and multi-scale coupling effects, presents formidable challenges for numerical modeling. Traditional computational fluid dynamics (CFD) approaches, despite their theoretical maturity, face significant limitations when addressing core two-phase flow problems such as interface tracking, phase-change heat transfer, and strong nonlinear coupling. Physics-informed neural networks (PINN) have emerged as a transformative computational paradigm that synergistically combines the universal approximation capabilities of deep neural networks with the fundamental principles of physics. By embedding governing partial differential equations, boundary conditions, and experimental observations directly into the neural network training process through carefully designed loss functions, PINN overcomes the limitations of both traditional numerical methods and purely data-driven approaches. The method offers distinct advantages, including mesh-free solutions, automatic differentiation for gradient computation, enhanced physical consistency, and superior performance on high-dimensional problems with complex geometries.

This comprehensive review systematically examines the theoretical foundations, algorithmic innovations, and practical applications of PINNs in two-phase flow modeling. The analysis encompasses key technical developments specifically tailored for two-phase flow systems, including interface representation methods, multi-scale modeling strategies for bridging microscopic interfacial physics with macroscopic flow behavior, adaptive weighting algorithms for balancing multi-physics loss terms, and stability enhancement techniques for handling density jumps and discontinuous material properties. The review comprehensively covers PINN applications across five major categories of two-phase flow systems. Gas-liquid flows are examined through applications in bubble dynamics, interface instabilities, and boiling heat transfer. Liquid-liquid systems are analyzed focusing on phase separation dynamics, fingering instabilities, and porous media applications. Gas-solid flow modeling encompasses particle transport, collision dynamics, and fluidization characteristics. Liquid-solid suspensions are investigated through sedimentation studies and rheological modeling. Phase change heat transfer systems integrate phase transition with transport phenomena, enabling coupled flow-thermal predictions with enhanced physical consistency. Performance evaluations across these applications reveal significant advantages of PINN methods compared to conventional CFD approaches, including computational speedup, prediction accuracy, and superior capability for handling inverse problems and parameter identification. The mesh-free nature of PINN proves particularly beneficial for problems involving complex topological changes, moving boundaries, and extreme aspect ratios.

Despite these advances, several critical challenges remain. Method universality is limited by the need for problem-specific network architectures and constraint formulations, restricting scalable deployment across diverse two-phase flow scenarios. Interface physics modeling requires further refinement to achieve higher interface sharpening, improved mass conservation, and enhanced long-term stability under extreme operating conditions. Current research primarily addresses traditional engineering two-phase flows with mature theoretical foundations, while exploration of frontier problems at micro scales and extreme conditions remains limited. Industrial deployment capabilities need strengthening through the development of real-time prediction systems, reliability assessment frameworks, and robust engineering implementation strategies. To address these challenges, future research directions emphasize the development of universal PINN frameworks capable of handling diverse two-phase flow configurations, integration of multi-source heterogeneous data for enhanced model robustness, breakthrough innovations in interface physics modeling, and systematic advancement of industrial deployment technologies. As artificial intelligence continues to deepen its integration with physical sciences, PINNs are positioned to play increasingly pivotal roles in two-phase flow research and engineering applications, providing powerful theoretical tools and technical support for innovation and industrial development.

physics-informed neural networks, two-phase flow, flow, heat transfer, machine learning

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