Mesh-Free Blood Flow Simulation for Liver Cancer Therapy Using Physics-Informed Neural Networks

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2026 JULY 19–22 VANCOUVER, BC
JOINT AAPM | COMP MEETING

INTRODUCTION

Hepatic Artery Vasculature

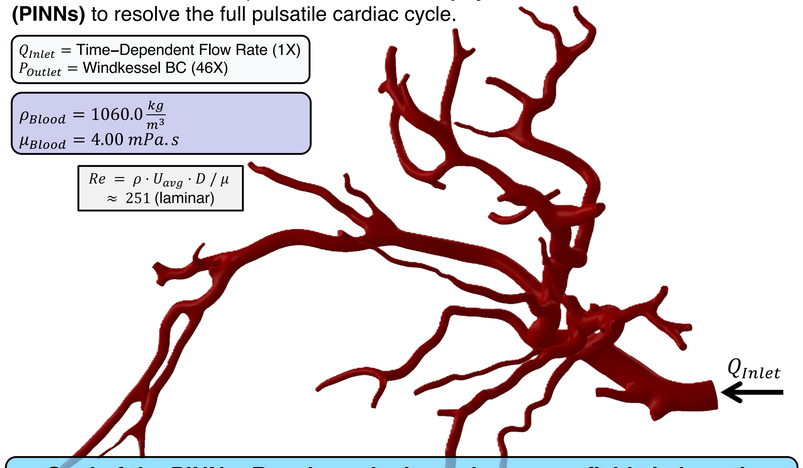
- Liver Y-90 radioembolization planning can be done with patient-specific hemodynamic modeling in the hepatic artery through computational fluid dynamics (CFD)
- Conventional mesh-based CFD is too slow and geometry-sensitive for clinical adoption

→ Motivates the development of mesh-free **physics-informed neural networks (PINNs)** to resolve the full pulsatile cardiac cycle.

Q_{Inlet} = Time–Dependent Flow Rate (1X)
P_{Outlet} = Windkessel BC (46X)

$\rho_{Blood} = 1060.0 \frac{kg}{m^3}$
$\mu_{Blood} = 4.00\ mPa.s$

$Re = \rho \cdot U_{avg} \cdot D / \mu \approx 251$ (laminar)



Goal of the PINNs: Resolve velocity and pressure fields in hepatic artery to predict blood flow and microsphere distribution

Fig. 1. Patient-specific hepatic arterial tree from contrast CT — one inlet, 46 outlets across segments S5-S8 and tumor.

Why Physics-Informed Neural Networks?

Physics-Informed Neural Networks (PINNs) embed the governing PDEs directly into the loss function, letting a single mesh-free network approximate velocity and pressure fields from a sparse set of reference samples.

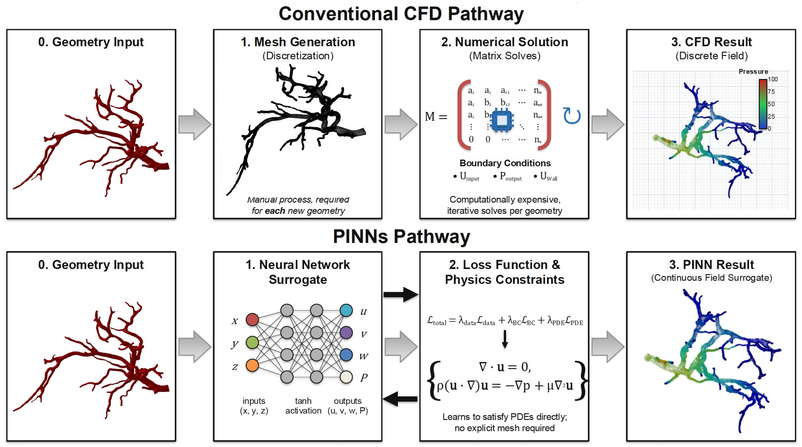


Fig. 2. Conventional CFD vs. PINNs: CFD needs mesh generation and matrix solves per geometry; PINNs provide a continuous field surrogate.

Scope of This Study

Key advantages for this problem:
1) Mesh-free evaluation on complex vessel geometry
2) Continuous, differentiable surrogate of u, v, w, p
3) Hybrid PDE + data loss reduces required training samples

In this work we train a 3D, transient, incompressible PINNs for a patient-specific hepatic artery tree using Nvidia PhysicsNeMo and validate against a (CFD) COMSOL finite-element solution on the same geometry.

AIMs: We combine:
1) Unsteady nondimensional Navier–Stokes residual loss via automatic differentiation
2) Pulsatile Fourier inlet, 46 Windkessel outlets, and no-slip walls
3) Validation vs. a CFD transient solution; Y-90 dose from per-outlet flow

PROPOSED MODEL

Governing Equations – Unsteady Navier–Stokes

Continuity (mass conservation) and $x/y/z$ momentum equations are written in nondimensional form with the characteristic diameter D, inlet mean velocity U_{avg}, and Reynolds number Re. CFD = ground truth to compute these parameters, done in COMSOL Multiphysics software.

Governing PDEs (Nondimensional, Constant Mass Density):

$$\nabla \cdot u^* = 0 \quad \textbf{(Continuity)}$$
$$\partial u^*/\partial t^* + (u^* \cdot \nabla)u^* = -\nabla p^* + (1/Re)\nabla^2 u^* \quad \textbf{(Momentum)}$$

Nondimensionalization:

$$x^* = x/D, u^* = u/U_{avg}, p^* = p/(\rho U_{avg}^2), Re = (\rho U_{avg} D)/\mu$$

Residuals (Automatic Differentiation): r_{cont}, r_x, r_y, r_z

Boundary Conditions: Inlet (Mass Flow Rate), Outlet (Windkessel), Walls (No-slips)

PINNs Architecture & Training

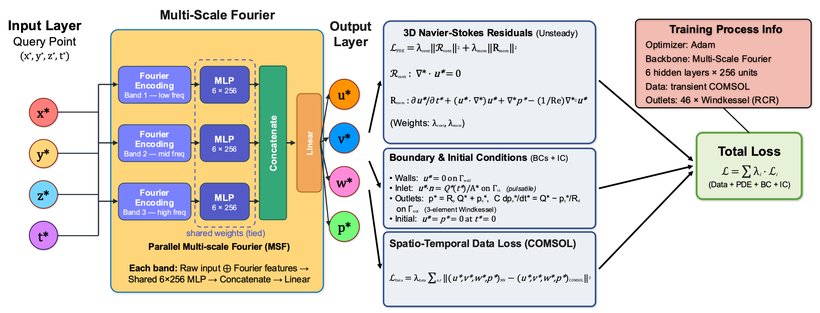


Fig. 3. PINNs architecture: a fully-connected network N_θ: $\mathbb{R}^3 \to \mathbb{R}^4$ maps nondimensional coordinates (x^*, y^*, z^*, t^*) to (u^*, v^*, w^*, p^*). 6 × 256 hidden units, SiLU activation, trained with Adam for ~858K steps.

Training loss: $L_{total} = \lambda_{PDE}L_{PDE} + \lambda_{BC}L_{BC} + \lambda_{IC}L_{IC} + \lambda_{Data}L_{Data}$
PDE residual: The average mean of $|r_{cont}|^2 + |r_x|^2 + |r_y|^2 + |r_z|^2$
Exponential Learning-rate schedule: $lr(t) = 10^{-3} \times 0.95^{t/20000}$
Outputs: u^*, v^*, w^*, p^* are the nondimensional velocity components and pressure predicted by the network at query point (x^*, y^*, z^*, t^*). Training uses Adam for $\sim 858K$ steps on COMSOL samples.

RESULTS

PINNs vs. COMSOL — Velocity & Pressure Fields

PINNs predictions match COMSOL across the full 3D hepatic-artery lumen for both velocity magnitude and pressure.
Point-wise error is well below 1% of the field range (pressure median 0.04%, velocity median 0.21%), and parity plots show strong linear agreement ($R^2 \geq 0.89$ for all components, 0.999 for pressure). Residual errors concentrate near sharp bifurcations, consistent with the highest local gradients.

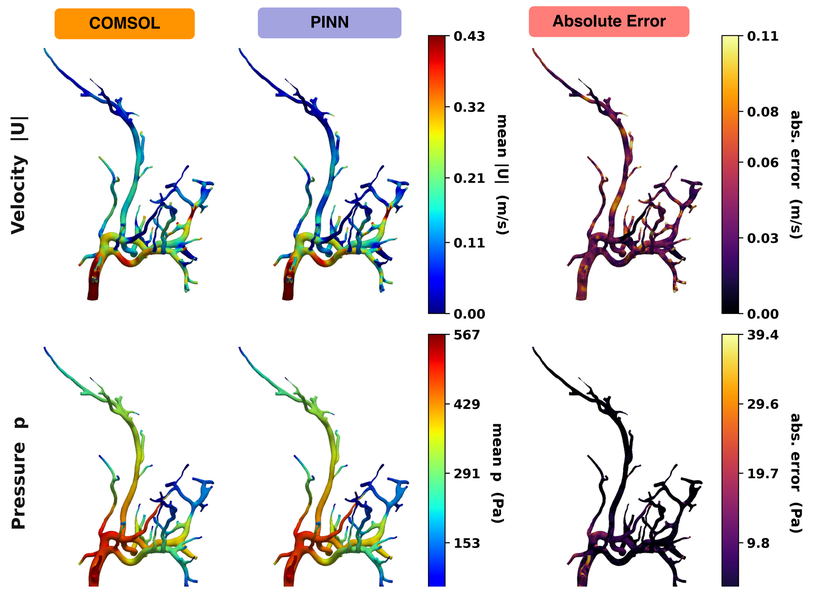


Fig. 4. Cycle-averaged velocity IU*I (top) and pressure (bottom): COMSOL vs. PINNs vs. absolute error.

The prescribed Fourier inlet waveform is recovered to 8.4% relative error, and the domain-mean velocity tracks COMSOL through systole and diastole. The 46 Windkessel (RC) outlets distribute flow across all branches — the cycle-mean split matches COMSOL to 26% L^1 error.

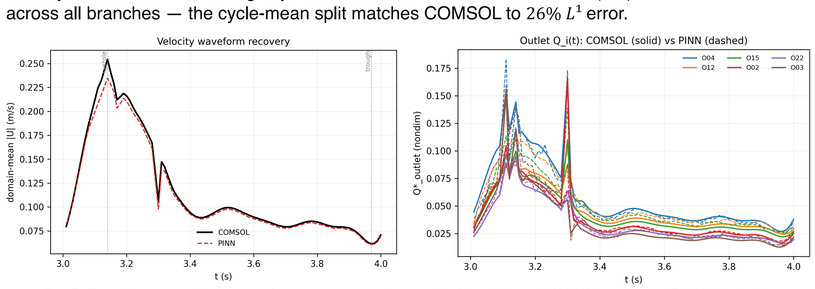


Fig. 5. Domain-mean velocity waveform recovery and per-outlet flow Q(t) — COMSOL (solid) vs. PINN (dashed).

Accuracy Across the Cardiac Cycle

- COMSOL provides reference u^*, v^*, w^*, p^*; the PINNs matches these while minimizing the Navier-Stokes residual.
- Over $\sim 858K$ Adam steps, total loss and PDE residuals each decay ~5 decades.
- Pooled relative L_2 vs. COMSOL: u^* 16.0%, v^* 29.9%, w^* 26.0%, p^* 1.7%.
- Inlet monitors track the prescribed pulsatile waveform (peak 2.17 & trough 0.67); wall $|U^*| \leq 0.13$ confirms BC enforcement.
- Per-timestep R^2 stays near unity, dipping only at peak systole where velocity gradients are steepest.

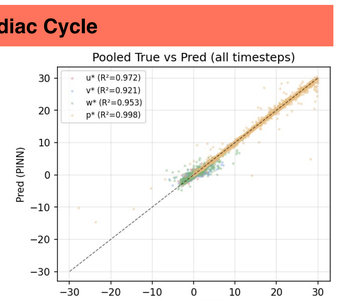


Fig. 6. Pooled PINN-vs-COMSOL parity over all timesteps: R² = 0.97/0.92/0.95/0.998 for u*/v*/ w*/p*.

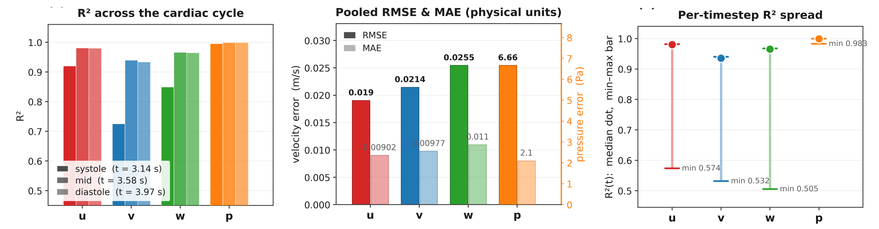
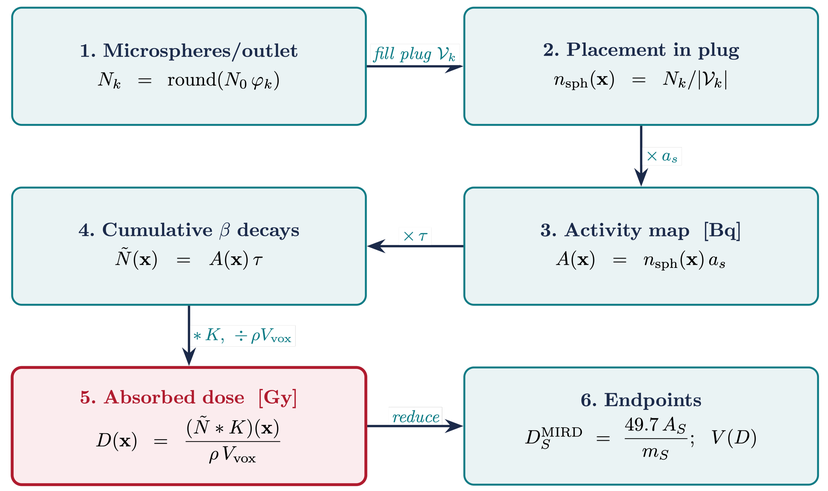


Fig. 7. Per-field accuracy vs. CFD over 218,437 mesh points × 97 clean timesteps: R² at systole/mid/diastole, pooled RMSE & MAE in physical units, and per-timestep R² spread.

From Flow to Y-90 Dose - Predicted Dose Distribution & DVH

Cumulative per-outlet flow sets each branch's microsphere share; spheres follow streamlines and a Y-90 dose-point kernel gives the 3-D dose map (Gy).



• φ_k = outlet flow fraction, • $\mathcal{V}_k$ = voxel set of plug k, • $*$ = 3-D convolution;
• K Y-90 β dosepoint kernel (GATE Monte Carlo).

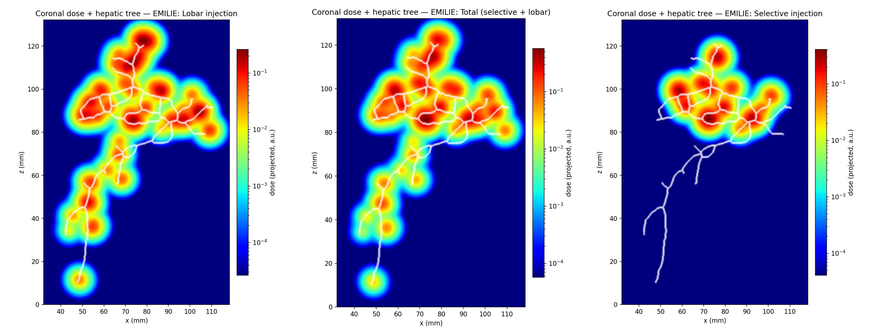


Fig. 8. Y-90 coronal dose over the hepatic arterial tree — lobar, combined (selective + lobar), and selective injection.

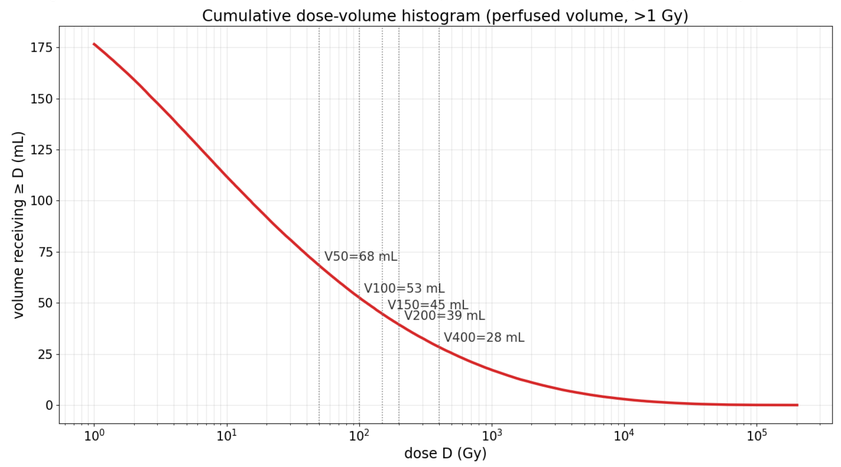


Fig. 9. Cumulative dose–volume histogram (perfused volume > 1 Gy, 177 mL): V50 / V100 / V200 = 68 / 53 / 39 mL.

CONCLUSIONS

1) Transient PINNs reproduces the cardiac-cycle hepatic flow field (R^2 = 0.97 / 0.89 / 0.93 / 0.999 for u / v / w / p; inlet flow within 8.4%, full COMSOL mesh).
2) Y-90 dose is robust to flow error; both PINNs and COMSOL dose agree within ~1– 2% despite a 26% per-outlet flow-split difference.
3) Peak-systole jet cores are the accuracy limit; the mesh-free surrogate otherwise generalizes across the lumen.

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This work was supported by funds from **NCI P30CA093373** and **U01CA289068**

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