GINNs: A GENERIC-Informed Neural-Networks methodology to learn thermodynamically sound rheological models

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We present a GENERIC-informed neural networks (GINNs) methodology for learning thermodynamically consistent constitutive relations for viscoelastic flows. The proposed closure framework enables the data-driven identification of tensorial constitutive equations that are fully compatible with the finite-volume discretization implemented in RheoTool/OpenFOAM. By embedding a thermodynamics consistent structure directly into a PINNs learning process, the method guarantees stability and transferability across geometries without retraining.

The framework builds upon the GENERIC formalism for complex fluids [1] and extends recent entropy-guided learning approaches [2]. In contrast to prior works limited to specific model forms, the present methodology enables the learning of arbitrary tensorial constitutive relations directly from data while preserving thermodynamic consistency. The closure procedure proceeds in two stages.

In **Stage 1**, the polymeric entropy potential is learned from stress data. Automatic differentiation is employed to compute entropy conjugate variables, ensuring that the resulting constitutive response satisfies the GENERIC reversible structure. This guarantees that the learned stress derives from a thermodynamically admissible entropy functional.

In **Stage 2**, the mobility matrix governing dissipation is inferred from the evolution of the conformation tensor through residual minimization. This stage generalizes deformation-dependent tensorial mobility and ensures positive entropy production. By learning the mobility operator rather than prescribing it, the framework recovers dissipative behavior consistent with the data while preserving thermodynamically imposed constraints.

As a result of the two stages, two neural networks are trained. These are evaluated locally (cell-by-cell) within RheoTool, without modifying the finite-volume discretization. The approach is therefore modular and solver-consistent, enabling seamless integration into existing CFD workflows.

Our methodology is first validated on the classical two-dimensional flow around a cylinder benchmark using Giesekus model [3]. Training data are generated from simulations of the Giesekus model for a Weissenberg number Wi = 1.5. The learned GINNs closure accurately reproduces velocity, pressure, and stress fields. The learned constitutive equation closely matches the reference model, with maximum relative root-mean-square errors (RRMSE) slightly above 1% (See **Figure 1**).

To assess ability of the trained model to be transferred to other geometries, the trained closure is applied without retraining to a cross-slot configuration. Despite the geometric and kinematic differences with respect to the cylinder case, the GINNs model accurately captures the stress and velocity distributions. Quantitative error metrics for the cross-slot simulations are summarized in **Table 1**, which reports RRMSE values for the principal flow variables. The spatial distribution of relative errors is shown in **Figure 2**, demonstrating uniformly low discrepancies across the computational domain.

The results highlight two key advantages of the proposed approach. First, embedding GENERIC structure into the learning procedure ensures thermodynamic admissibility and numerical robustness. Second, the learned closure exhibits geometry-agnostic transferability, maintaining accuracy in unseen configurations without additional training.

Overall, the proposed GINNs framework provides a physically grounded, data-driven pathway for constructing reusable viscoelastic constitutive relations. By combining thermodynamic structure with neural networks approximation capabilities, the method delivers accurate and stable closures suitable for finite-volume CFD simulations across varying flow rates and geometries.

References

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Figures and Tables

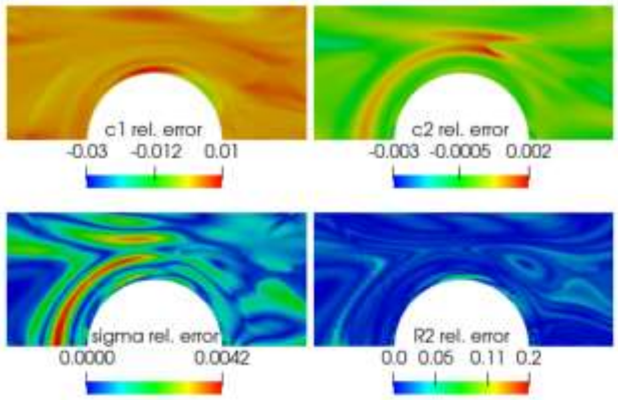

Figure 1. Relative-error fields for Wi=1.5: FV reference versus PINN-closed solution after Stage 1 and Stage 2 training.

Table 1. Cross-slot flow solved with the cylinder-trained GINN closure (Wi = 0.25). Relative root-mean-square error (RRMSE) for relevant flow variables.

Variable	RRMSE
U	3.75×10^{-5}
c_1	5.00×10^{-4}
c_2	1.10×10^{-3}
τ_1	5.96×10^{-4}
τ_2	1.92×10^{-3}
σ_1	8.84×10^{-4}
σ_2	1.57×10^{-3}
$R_{2,1}$	3.01×10^{-3}
$R_{2,2}$	1.12×10^{-2}

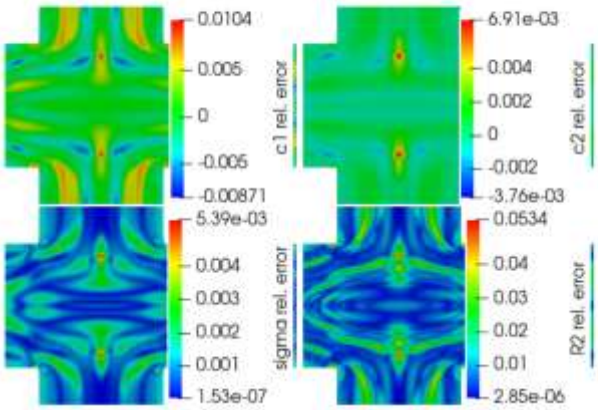

Figure 2. Relative-error fields for Wi=0.25 cross-slot: FV reference versus PINN-closed solution.