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Research paper

Pipe flow of thixotropic fluids: Experiments, simulations and neural networks

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ABSTRACT

Thixotropy refers to the time-dependent evolution of a material's microstructure, where structural agglomerates are progressively broken down under shear and rebuild when flow ceases. This study examines how such microstructural dynamics influence the transient pressure response of thixotropic yield stress fluids in laminar pipe flow. Experiments on Laponite suspensions performed with a custom built pipe rig reveal a pronounced decay in pressure drop over time at constant flow rate, reflecting shear induced structural breakdown. Complementary computational fluid dynamics simulations based on the Houska thixotropic constitutive model accurately reproduce the experimentally measured transient pressure drop evolution, with relative errors below 5% for most flow conditions, and elucidate the interplay between structural breakdown and recovery that governs the evolution of flow. The simulations capture the reduction of plug flow velocity profile due to thixotropic effects as flow rate increases, accompanied by a reduction of unyielded regions. To reduce experimental effort and computational cost, a feed-forward neural network surrogate trained on a limited set of validated experimental and simulated data accurately predicts the transient pressure drop evolution across a wide range of flow conditions with greater than 95% accuracy. The integrated experimental, computational, and data-driven framework provides an efficient approach for predicting transient pressure losses in thixotropic pipe flow, substantially reducing the need for extensive experiments and computationally intensive CFD simulations.

1. Introduction

Thixotropy is a common feature of many industrially relevant fluids, including drilling muds, cemented tailings pastes, crude oils, paints, and food products (Barnes, 1997). These materials exhibit time-dependent rheology, whereby their microstructure progressively breaks down under shear, leading to a reduction in viscosity, and subsequently rebuilds when the flow ceases or the material is left at rest (Amini et al., 2024; Mishra et al., 2025a). This coupling between flow history and microstructural evolution makes thixotropic fluids particularly challenging to transport through pipelines, where accurate prediction of pressure losses is essential for process design, energy efficiency, and operational safety. Consequently, the pipe flow of thixotropic fluids has been investigated extensively through experimental, theoretical, and computational approaches.

Experimental studies have shown that the effects of thixotropy are most pronounced in the laminar flow regime, where the evolving material structure gives rise to behaviour that cannot be described

by conventional steady-state rheological models. Early Laser Doppler Anemometry (LDA) measurements showed that Laponite suspensions could be reasonably described by Herschel-Bulkley rheology at low Reynolds numbers (Re), whereas at higher Re the coupling between shear and structural evolution led to deviations from steady-state behaviour and drag-reduction effects, highlighting the need for structural constitutive models (Escudier and Presti, 1996). In contrast, studies of turbulent recirculating flows reported flow characteristics broadly comparable to those of water, with only modest differences in the Reynolds stress distribution (Pereira and Pinho, 2001). These studies established that the time-dependent evolution of the material microstructure plays a fundamental role in governing pipe-flow behaviour and motivated the development of constitutive models capable of describing structural breakdown and rebuilding.

To describe the time-dependent rheology of thixotropic fluids, several structural constitutive models have been developed, among which the Moore, Houska, and Moore-Mewis-Wagner (MMW) models are

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the most widely adopted (Mewis and Wagner, 2009; Ahmadvpour and Sadeghy, 2013). These models introduce an internal structural parameter that evolves through competing breakdown and rebuilding processes, enabling the transient rheological response of thixotropic materials to be described within a continuum framework. Owing to their versatility, they have subsequently been employed in analytical and numerical studies of pipe flow to investigate the influence of structural evolution on fluid transport. Linear stability analysis on pipe flow with the Moore model concluded that thixotropy has a destabilizing influence, lowering the critical Reynolds number for unstable flow compared to shear thinning or yield stress fluids alone (Nahavandian et al., 2018). Furthermore, extensive analysis has been performed on unsteady flows in slowly varying pipes (whose cross-sectional area or curvature changes gradually along the flow direction) and oscillatory pipe flows, mapping weak to strong thixotropic regimes for both MMW and Houska models (Croudace et al., 2017). More recently, the concept of thixotropic pumping has been introduced, demonstrating that under asymmetric oscillatory forcing (time-periodic pressure gradient), thixotropy can generate net transport in a pipe even when a non-thixotropic fluid would exhibit no net transport or zero mean flow (Pritchard et al., 2020). Together, these studies show how thixotropic structure-flow coupling can alter not just rheology, but also flow stability, transport, and pumping mechanisms.

Building on these constitutive models, Computational Fluid Dynamics (CFD) has become a powerful tool for investigating thixotropic pipe flows under realistic operating conditions. By coupling the governing flow equations with structural constitutive models, CFD enables prediction of the evolving flow and rheological fields. Most studies have focused on steady or quasi-steady behaviour, examining quantities such as pressure losses, velocity profiles and viscosity distributions, that are often difficult to access experimentally. For example, finite-volume simulations of cemented tailings paste demonstrated that incorporating thixotropic breakdown-rebuilding kinetics significantly improved the prediction of pressure losses compared with equilibrium or Bingham plastic models (Zhang et al., 2023). At a more fundamental level, Direct Numerical Simulations (DNS) based on the Moore model have been employed to investigate the interaction between turbulence and microstructural evolution, providing detailed insights into Eulerian and Lagrangian structural dynamics, Reynolds-stress transport, and drag reduction mechanisms in turbulent pipe flow (Yousuf et al., 2025). These studies have demonstrated that CFD provides a valuable framework for investigating the steady state flow behaviour of thixotropic fluids using structural constitutive models.

Despite the rich scientific literature on thixotropic flow, a significant gap remains. Most experimental studies have focused on velocity profiles, turbulence statistics, or steady-state friction factors, while computational studies have primarily investigated rheology, flow stability, and statistically stationary flow behaviour. In comparison, only a few studies have examined the transient pipe flow of thixotropic fluids. In a notable example, drilling fluids were investigated in a hydraulic loop, demonstrating experimentally that the frictional pressure loss decreases with time as the fluid structure progressively breaks down under continuous flow (Olusola et al., 2025). However, the study did not include computational modelling to validate whether CFD simulations incorporating thixotropic constitutive models could quantitatively reproduce the experimentally observed transient pressure-drop evolution.

Recently, artificial intelligence (AI) and machine learning approaches have been explored as surrogate models for predicting the flow dynamics of thixotropic fluids in rheometric flows (Mishra et al., 2025b). Beyond rheology, machine learning techniques have also been successfully coupled with computational fluid dynamics for a wide range of fluid mechanics and heat-transfer problems, including nanofluid transport, magnetohydrodynamic flows, arterial flow, and convective heat transfer, demonstrating their ability to substantially reduce computational cost while maintaining high predictive accuracy (Wang

et al., 2025; Hussain et al., 2025; Kumar et al., 2025; Ahmed et al., 2026; Mohammed et al., 2025, 2026). Physics-informed neural networks (PINNs) and rheology-informed neural networks (RhINNs) have emerged as powerful tools for incorporating constitutive equations and governing laws directly into the training process, enabling accurate forward and inverse solutions of rheological problems (Saadat et al., 2023). Digital rheometer twins based on rheology-informed graph neural networks have been introduced, demonstrating that limited experimental data can be leveraged to learn hidden rheological laws and predict flow responses across protocols (Mahmoudabadbozchelou et al., 2022). Similar frameworks have been applied to cementitious and slurry systems, where PINNs and Navier–Stokes-informed neural networks (NSINNs) have successfully predicted rheological and flow behaviour with reduced computational cost compared to CFD (Zhang et al., 2025; Yan et al., 2025). These developments highlight the growing role of AI driven surrogates in modelling rheologically complex fluids. However, while such methods provide efficient alternatives to high-fidelity simulations, they have not yet been applied to directly predict the transient evolution of pressure drop in pipe flow of thixotropic fluids.

Motivated by these challenges, the present work combines experiments, constitutive CFD modelling, and machine learning to investigate the transient pipe flow of a model thixotropic fluid. First, controlled pipe-flow experiments are performed to quantify the temporal evolution of pressure drop under constant flow conditions. A laponite suspension is used as a model thixotropic material owing to its well-established nonlinear and time-dependent rheological behaviour (Amini et al., 2024; Mishra et al., 2025b). The experimental pressure drop evolution, arising from the interplay between structural breakdown and recovery, is then reproduced using CFD simulations based on the Houska structural constitutive model, providing quantitative validation of the predicted transient pressure evolution. Finally, a feed-forward neural-network surrogate is trained using the experimental and computational data to accurately predict transient pressure-drop evolution across a range of flow conditions with substantially reduced computational cost. To the best of our knowledge, this is the first study to integrate transient pipe-flow experiments, validated constitutive CFD simulations, and a neural-network surrogate within a unified framework for predicting the time-dependent pressure loss of a thixotropic fluid. Beyond demonstrating the transient pressure evolution, the proposed framework provides an efficient route for predicting and optimizing the transport of thixotropic fluids in pipe flow systems through the combined use of constitutive modelling and machine learning.

2. Materials and methods

2.1. Preparation of laponite suspension

Laponite suspension was prepared by dispersing an appropriate amount of Laponite RD powder (Conservation Resources Ltd, UK) in 60 L of deionized water and mixed at 2000 RPM using a paddle mixer (Mixer Flex MXE1602, Ahlsell, Sweden) for 30 min to homogenize the mixture. The solution was allowed to rest for 72 h to achieve a stable gel with appropriate viscosity. Laponite is a synthetic hectorite clay composed of disk-shaped nanoparticles that exhibits thixotropy when prepared as a solution (Amini et al., 2024).

2.2. Rheological characterization

Rheological properties were measured using an MCR702e Space rotational rheometer (Anton Paar, Graz, Austria), with a profiled bob and cup geometry (CC27/P6) to minimize slip, in a single motor-transducer configuration. The diameters of the bob and cup were 27 mm and 29 mm (cup inner diameter) respectively (1 mm gap). To maintain the measuring temperature constant at 23 °C, a C-ETD200/XL electrical

temperature device was utilized. The flow curve was measured in a rate controlled steady shear test where the shear rate was ramped down in from 10^3 to 10^{-2} . The sample was sheared for 30 s at each shear rate to achieve near steady state, as established in our previous work (Amini et al., 2024).

2.3. Pipe flow experiments

A custom built pipe rig was developed in collaboration with Tetra-Pak Processing Systems (Lund, Sweden) for flow experiments. The rig consisted of a 200 L balance tank connected to a rotary positive displacement screw pump (Knoll Maschinenbau GmbH, type MX 30-S-50/20, maximum frequency 115 Hz). The pump delivered fluid into one of five interchangeable straight stainless steel tubes (length 3400 mm) with inner diameters ranging from 14–51 mm. Flow direction to the desired tubes was controlled by a system of ball valves located before and after the tubes, enabling rapid switching between different pipe diameters. A schematic illustration of the pipe rig is presented in Fig. 1.

Flow rate was measured downstream of the balance tank with a flow meter (Endress and Hauser, Basel-Country, Switzerland), providing accurate real time monitoring during operation. Two thermocouples positioned immediately before and after the flow meter recorded the fluid temperature continuously to ensure stable thermal conditions during circulation. To measure the pressure drop across the tubes, three metal membrane pressure transducers (Endress and Hauser, Basel-Country, Switzerland) were installed 200 mm downstream of the pipe inlets, with 600 mm spacing between each transducer. This arrangement enabled time resolved differential pressure monitoring with an accuracy of 0.05%. Prior to each experiment, the pressure sensors were set to zero with the tubes empty to ensure proper baseline referencing. The differential pressure measurement system was further calibrated using water (viscosity = 1.0 mPa s) at 22.7 °C, and a relative humidity of 44.5%. The flow rate was controlled by a variable frequency drive (Nordborg, Denmark), which adjusted the pump speed until the target steady-state condition was achieved. Pressure drop, flow rate, and temperature data were collected using a NiLabView 2018 data acquisition system (National Instruments, USA) at a sampling frequency of 1 Hz.

For all experiments, the test Laponite suspension was carefully poured into the balance tank and allowed to rest to eliminate the shear history introduced during pouring. The fluid was then gently pumped into the 14 mm diameter tube at a low flow rate of 300 L/h until the tube was completely filled. To ensure uniform filling and structural relaxation, the system was left to equilibrate for 30 min under quiescent conditions. Subsequent measurements were performed in circulation mode i.e. the sample exiting the outlet of the tube was collected back into the balance tank and recirculated through the same tube. Each circulation experiment was conducted for 300 s to obtain reproducible flow and pressure drop data.

3. Numerical modelling

3.1. Governing equations

Under isothermal conditions and test fluid incompressibility assumption, the governing equations reduce to the incompressible Navier-Stokes, momentum balance (1) and continuity (2) equations.

$$\rho \left(\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} \right) = -\nabla p + \nabla \cdot \boldsymbol{\tau} + \rho \mathbf{g}, \quad (1)$$

$$\nabla \cdot \mathbf{u} = 0, \quad (2)$$

where $\mathbf{u}$ is the velocity vector, p the pressure, ρ the fluid density, $\mathbf{g}$ is the acceleration due to gravity, and $\boldsymbol{\tau}$ the deviatoric stress tensor. For Newtonian fluids, the constitutive law is simply $\boldsymbol{\tau} = 2\eta\mathbf{D}$, where η is a constant viscosity and

$$\mathbf{D} = \frac{1}{2} (\nabla \mathbf{u} + (\nabla \mathbf{u})^T), \quad (3)$$

the rate of strain tensor, i.e. the symmetric part of the velocity gradient tensor. Its second invariant defines a scalar measure of the local shear rate,

$$\dot{\gamma} = \sqrt{2 \mathbf{D} : \mathbf{D}}, \quad (4)$$

where “:” denotes the double tensor contraction (double-dot product). For non-Newtonian fluids with complex rheology such as shear thinning, viscoplasticity, and thixotropy, the viscosity is no longer constant but depends on both the instantaneous shear rate and an evolving structural parameter $\lambda \in [0, 1]$. The generalized constitutive form is therefore written as

$$\boldsymbol{\tau} = 2 \eta_{\text{eff}}(\dot{\gamma}, \lambda) \mathbf{D}, \quad (5)$$

where $\eta_{\text{eff}}(\dot{\gamma}, \lambda)$ is the apparent viscosity, a nonlinear function of the shear rate $\dot{\gamma}$ and the structural state λ . The parameter λ represents the integrity of the microstructure, with $\lambda = 1$ corresponding to a fully structured state and $\lambda = 0$ to a completely broken one. Eqs. (1)–(5) provide the general framework into which specific constitutive laws, such as the Houska model, can be introduced to capture the complex rheological properties of a given fluid.

3.2. Houska constitutive model

The Houska model is a phenomenological constitutive model that describes the viscosity of a fluid as a function of the applied shear rate and the resulting structural state, $\lambda \in [0, 1]$. The Houska model can be non-rigorously derived starting from the well known power law constitutive relation for shear thinning fluids given by,

$$\eta = m \dot{\gamma}^{n-1}, \quad (6)$$

where m and n are the consistency and flow index respectively; $n < 1$ describes the shear thinning behaviour of the fluid with $n = 1$ and $n > 1$ representing a Newtonian and shear thickening fluid respectively. The contribution due to yield stress can be easily incorporated by using the Herschel-Bulkley model,

$$\eta = \frac{\sigma_y}{\dot{\gamma}} + m \dot{\gamma}^{n-1}, \quad (7)$$

where σ_y represents a (constant) yield stress. For a thixotropic fluid, the yield stress and consistency index are assumed to have an additional linear time-dependent structural contribution.

$$\sigma_y(\lambda) = \sigma_{y,0} + \sigma_{y,t} \lambda, \quad (8)$$

$$m(\lambda) = m_{y,0} + m_{y,t} \lambda \quad (9)$$

The Houska constitutive model is obtained by substituting Eqs. (8)–(9) in Eq. (7)-

$$\eta(\dot{\gamma}, \lambda) = \frac{\sigma_{y,0} + \sigma_{y,t} \lambda}{\dot{\gamma}} \left[1 - e^{-m_p \dot{\gamma}} \right] + (m_{y,0} + m_{y,t} \lambda) \left(\frac{\dot{\gamma}}{\dot{\gamma}_{\text{ref}}} \right)^{n_f - 1}, \quad (10)$$

where n_f is the flow index, $\dot{\gamma}_{\text{ref}}$ the reference shear rate at which the material yields, and m_p a regularization parameter used to avoid the singularity at the yield point and allow a smooth transition from elastic to plastic deformation. With $\sigma_{y,t}(\lambda) = 0$ the law reduces to a shear thinning power law; with large m_p it approaches the Herschel–Bulkley form; and with $\sigma_{y,t}(\lambda) = 0$, $n_f = 1$ it reduces to a Newtonian fluid. Thus, the Houska model embeds classical rheologies as special cases while allowing their properties to vary dynamically with transient structural evolution. The regularization parameter m_p removes singularities at low shear rates, with larger values sharpening the yield transition but increasing numerical stiffness.

The structural parameter evolves according to the following differential equation-

$$\frac{d\lambda}{dt} = k_f(1 - \lambda) - k_b \lambda \left(\frac{\dot{\gamma}}{\dot{\gamma}_{\text{ref}}} \right)^{n_b - 1} \quad (11)$$

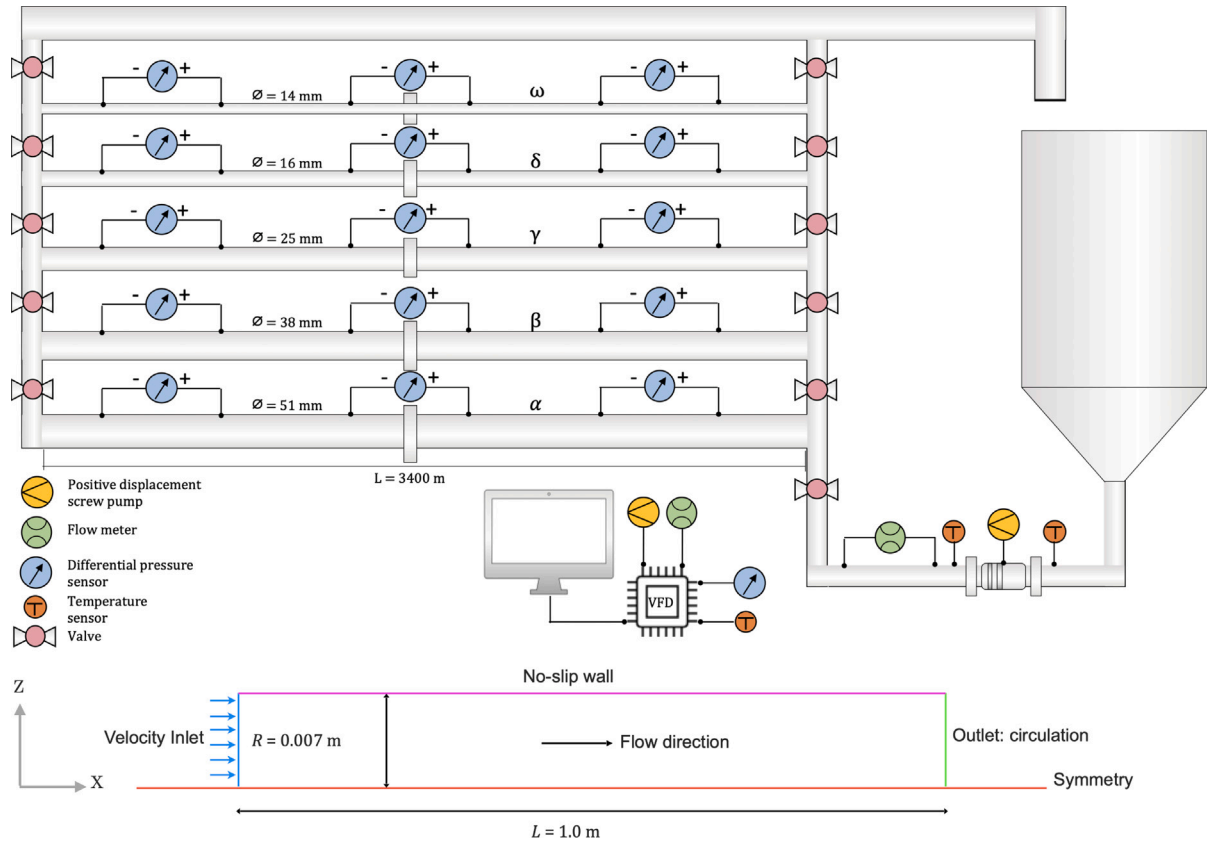


Fig. 1. Schematic of the experimental and computational pipe flow domain. The system consists of a balance tank connected to a positive displacement pump that drives the fluid through one of several interchangeable stainless-steel tubes (length = 3400 mm, inner diameter = 14–51 mm).

where k_f and k_b are the recovery and breakdown coefficients, respectively, and n_b the shear dependent breakdown coefficient. This equation couples the time evolving microstructure to the flow: shear promotes breakdown and quiescence promotes rebuilding. The resulting λ -field modifies both yield stress and consistency index. Coupled with the Navier–Stokes equations, the Houska model provides a closed CFD model that captures shear thinning, yielding, and time-dependent structural evolution in a unified framework.

3.3. Numerical implementation

The simulations are performed using the IPS IBOFlow solver (Mark et al., 2025), where the incompressible Navier–Stokes equations, Eq. (1) and (2), are discretized on a collocated Eulerian octree background grid using the finite-volume method. A second-order accurate scheme is used for both convective and diffusive fluxes. Grid refinement is applied in regions of high velocity gradients to adequately resolve boundary layers, see Fig. 3. Pressure-velocity coupling is achieved using the SIMPLEC algorithm (Doormaal and Raithby, 1984). To avoid pressure-velocity decoupling in the collocated arrangement, face velocities are interpolated using the balanced-force momentum-weighted interpolation scheme (Bartholomew et al., 2018). Immersed boundary conditions are imposed using the implicit mirroring immersed boundary method (Mark and van Wachem, 2008; Mark et al., 2011).

3.3.1. Time stepping and convergence

An implicit first-order Euler time-integration scheme is used for all simulations. A fixed time-step is chosen to ensure a Courant number $Co < 1$ in the most refined grid regions. Each time step is iterated until the normalized continuity equation error is below 10^{-6} .

3.3.2. Boundary and initial conditions

For pipe-flow simulations, the velocity is set at the inlet, while a constant-pressure boundary condition is applied at the outlet. No-slip immersed boundary conditions are imposed on all solid walls. For cyclic pipe flow, fluid exiting the outlet is reintroduced at the inlet with its structural state preserved. The velocity field is initialized with the inlet velocity, and pressure is initialized uniformly. The structural parameter is initialized as $\lambda = 1$ (fully structured) unless otherwise stated.

3.3.3. Lagrangian-Eulerian treatment of the constitutive model

The Houska constitutive equation, Eq. (10), and the structural evolution equation, Eq. (11), are solved in a Lagrangian framework (Ingelsten et al., 2019, 2020). The Lagrangian nodes are convected by the local fluid velocity using a second-order accurate integration scheme. A node density of 5 nodes per mm^3 is used, corresponding to a spacing of $h = 0.5 \text{ mm}$. Doubling the node density changes the predicted pressure drop by less than 1%. No regularization parameter was needed to avoid numerical oscillations at steep shear-rate gradients, the small permanent yield stress $\sigma_{y,0}$ was sufficient.

3.3.4. Computational cost

A typical simulation uses approximately 100 000 Eulerian cells and 130 000 Lagrangian nodes. On an NVIDIA GPU (model NVIDIA GeForce RTX 3090), one physical second of flow requires approximately 1.5 minutes of wall-clock time. A full simulation of 300 s requires roughly 7–11 h.

3.3.5. Model assumptions

The fluid is assumed incompressible and isothermal. Hence, the density and material parameters are constant. These assumptions are consistent with previous studies using the same framework (Ingelsten et al., 2019, 2020).

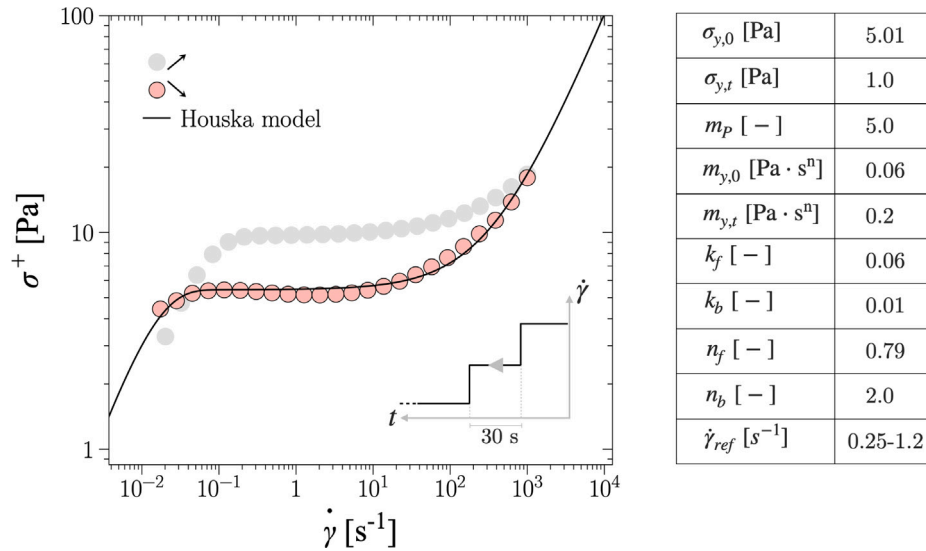


Fig. 2. Figure showing ramp up (grey circles) and ramp down (pink circles) steady state rate controlled stress evolution of 2 wt% Laponite suspension, measured with a time step size of 30 s per shear rate. The solid line represents the Houska thixotropic model fit to the ramp down flowcurve, and the parameter values are presented in the table to the right.

4. Results and discussion

4.1. Rheological characterization

Fig. 2 presents the steady-state flow curve of a 2 wt% Laponite suspension. In our previous work, we demonstrated through constant shear rate tests that a duration of 30 s is sufficient for Laponite suspension to attain a near steady state response in simple shear. The flow curve displays a power law dependence at high shear rates and a plateau at intermediate shear rates, both characteristic features of shear thinning yield stress fluids. The repeatability of the rheological measurements is demonstrated in the Supplementary Information (Fig. S1 b). At $\dot{\gamma} \sim 10^{-1} \text{ s}^{-1}$, the suspension yields and transitions from predominantly elastic to plastic deformation. This gradual yielding process is typical of viscoelastic fluids and can be described either using dedicated viscoelastic constitutive models or, alternatively, by introducing a regularization term to avoid singularities. Steady shear rate controlled test was performed by ramping the shear rate upward (indicated by grey circles) followed by a downward ramp, which produced a hysteresis loop. The presence of this loop confirms the thixotropic nature of the suspension. The degree of thixotropy was quantified by calculating the area enclosed by the loop, yielding a value of 2607 Pa s^{−1}.

The model parameters were obtained by fitting Eq. (10) to the ramp down flow curve using a trust region reflective nonlinear least squares algorithm. Logarithmic residuals were minimized to ensure uniform weighting across the investigated shear rate range. Multiple randomized initial parameter sets and physically admissible parameter bounds (Table S1) were employed to improve robustness. The optimal fit yielded RMSE = 0.359 and $R^2 = 0.99845$. Additional information regarding the goodness of fit and parameter sensitivity is provided in the Supplementary Information (Fig. S1 c,d).

4.2. Meshing

Fig. 3 illustrates the computational mesh and the effect of mesh refinement on the simulated pressure drop, ΔP , with time for an inlet flow rate of 1100 L/h. A structured mesh with local refinement was employed to resolve the near wall region and capture velocity gradients accurately, as shown in Fig. 3(a). The pressure evolution over time for different base cell sizes and refinement levels is presented in Fig. 3(b). Simulations performed with a base cell size of

10^{-2} (black and orange curves) show a higher predicted pressure drop compared to those with a finer base cell size of 10^{-3} (grey and blue curves). Increasing the refinement level from 1 to 2 significantly reduces the pressure drop, and further refinement produces only marginal differences between the curves, indicating numerical convergence. The comparison demonstrates that a refinement level of 2 with a base cell size of 10^{-3} provides a sufficiently accurate and mesh-independent solution while maintaining computational efficiency. Mesh independence was evaluated for the highest investigated flow rate, corresponding to the most demanding flow condition with the largest velocity and structural gradients. Since the same computational domain, numerical settings, and mesh-generation strategy were employed for all simulations, the selected mesh was used consistently throughout the investigated flow-rate range.

4.3. Pressure drop: Experiments, modelling and simulations

Fig. 4(a) presents a comparison between experimentally measured pressure drops and CFD simulations over 300 s of flow time at three different flow rates for a pipe diameter of 14 mm. The experimental repeatability of the transient pressure-drop measurements is demonstrated in the Supplementary Information (Fig. S1a), where the mean response and deviations obtained from three independent experiments are presented. To characterize the system, we introduce three dimensionless numbers. The Reynolds number (Re), Bingham number (Bi), and thixotropy number (Tx) are used as representative dimensionless parameters to facilitate comparison between different flow conditions, following the convention widely adopted in previous studies of thixotropic and yield-stress fluid flows.

$$Re = \frac{\rho V_{\max} D}{\eta}, \quad Bi = \frac{\sigma_y}{\eta \dot{\gamma}}, \quad Tx = \frac{A_{\text{loop}}}{\eta \dot{\gamma}^2}, \quad (12)$$

where ρ is the fluid density ($\rho = 1003.2 \text{ kg/m}^3$ (Amini et al., 2024)), $V_{\max}$ is the maximum inlet velocity, D is the hydraulic diameter, and η is the shear viscosity obtained from the flow curve at the wall shear rate $\dot{\gamma} = 4Q/\pi R^3$, with R being the tube radius. The yield stress σ_y is extracted by fitting the Herschel-Bulkley model to the flow curve, while A_{loop} corresponds to the hysteresis loop area, quantifying the extent of thixotropy.

The pressure drop, ΔP , increases with increasing flow rate and Re but decreases with time due to the thixotropic nature of the material.

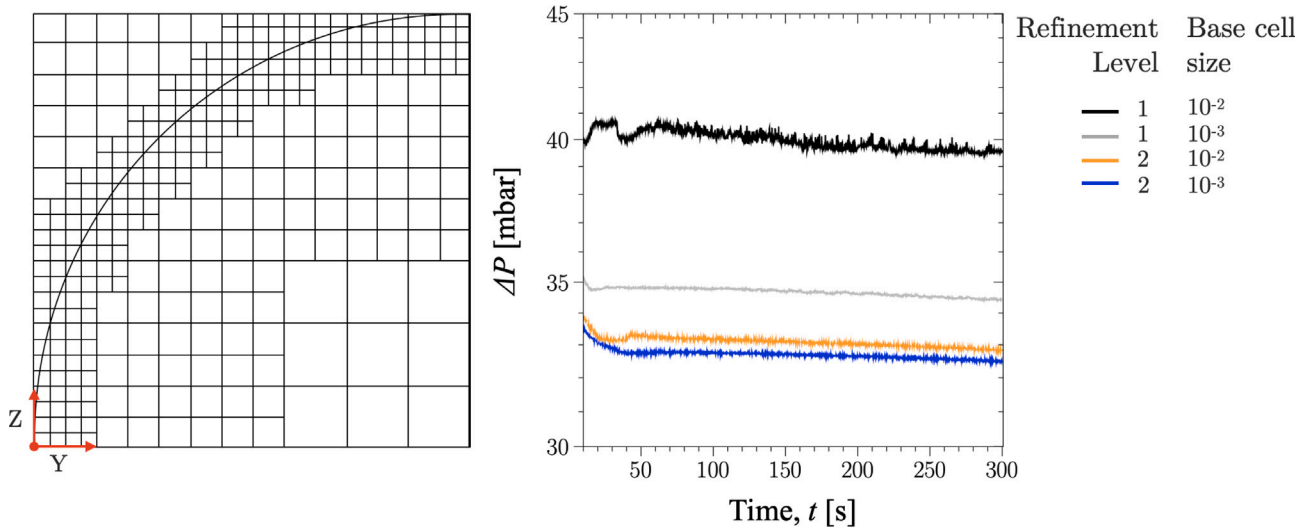


Fig. 3. Computational mesh and mesh independence analysis. (a) Structured mesh of the pipe domain with local refinement near the wall to accurately resolve the boundary layer. (b) Temporal evolution of the simulated pressure drop, ΔP , for different base cell sizes and refinement levels at an inlet flow rate of 1100 L/h.

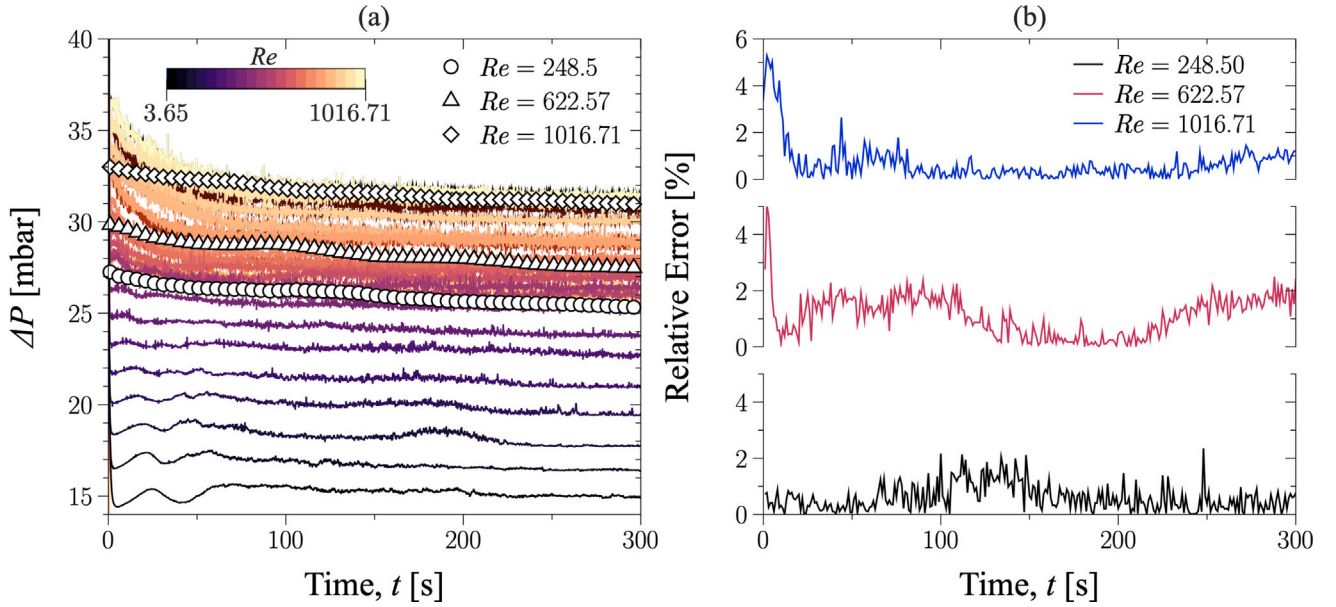


Fig. 4. Pressure drop as a function of time for different Reynolds numbers. (a) Comparison between experimental measurements (symbols) and CFD simulations (solid lines) over 300 s, showing the decrease in ΔP due to thixotropic breakdown and recovery effects. Results are presented for $Re \in [3.65, 1016.71]$. (b) Relative error between experimental data and model predictions for three representative cases ($Re = 248.50$, 622.57 , and 1016.71).

At the onset of flow, ΔP decays sharply, reflecting the rapid breakdown of the material's internal microstructure under shear. This initial decay phase is dominated by structural breakdown processes, where the fluid network is disrupted and viscosity decreases accordingly. As the flow progresses at constant flow rate, the rate of structural breakdown slows down and eventually competes with structural recovery. This interplay leads to a gradual reduction in the rate of ΔP decay, and the system approaches a quasi-steady state after $t \sim 300$ – 400 s. Importantly, this transition highlights the dynamic balance between breakdown and recovery mechanisms: while breakdown dominates at short times, recovery limits further reduction in pressure drop at long times.

The CFD simulations employ parameters from the Houska thixotropic model (see Fig. 2) to predict the pressure drop evolution in the laminar flow regime across a Re range $Re \in [3.65, 1016.71]$. At the lowest Re , ΔP shows fluctuations during the first 80 s, after which only a slight decay is observed that levels off beyond 200 s. This behaviour reflects the

relatively low shear rates at small Re , which are insufficient to induce significant structural breakdown. As a result, the pressure drop remains comparatively stable and does not exhibit strong thixotropic decay. At intermediate Re , a sharp decay of ΔP was observed initially, reflecting enhanced breakdown due to higher shear rates. At the highest Re , ΔP exhibits a steep initial drop, indicating rapid and extensive structural breakdown driven by strong shear forces. In this regime, the pressure drop is not only higher in magnitude but also more strongly time-dependent, reflecting the accelerated kinetics of structural evolution. Thus an increase in Re is accompanied by decreasing Bi and Tx , reflecting a reduced relative influence of yield stress and structural recovery. Consequently, the system transitions from a weakly evolving regime, where recovery remains significant, to a strongly thixotropic regime dominated by rapid structural breakdown. To further visualize the transient structural dynamics predicted by the Houska model, a

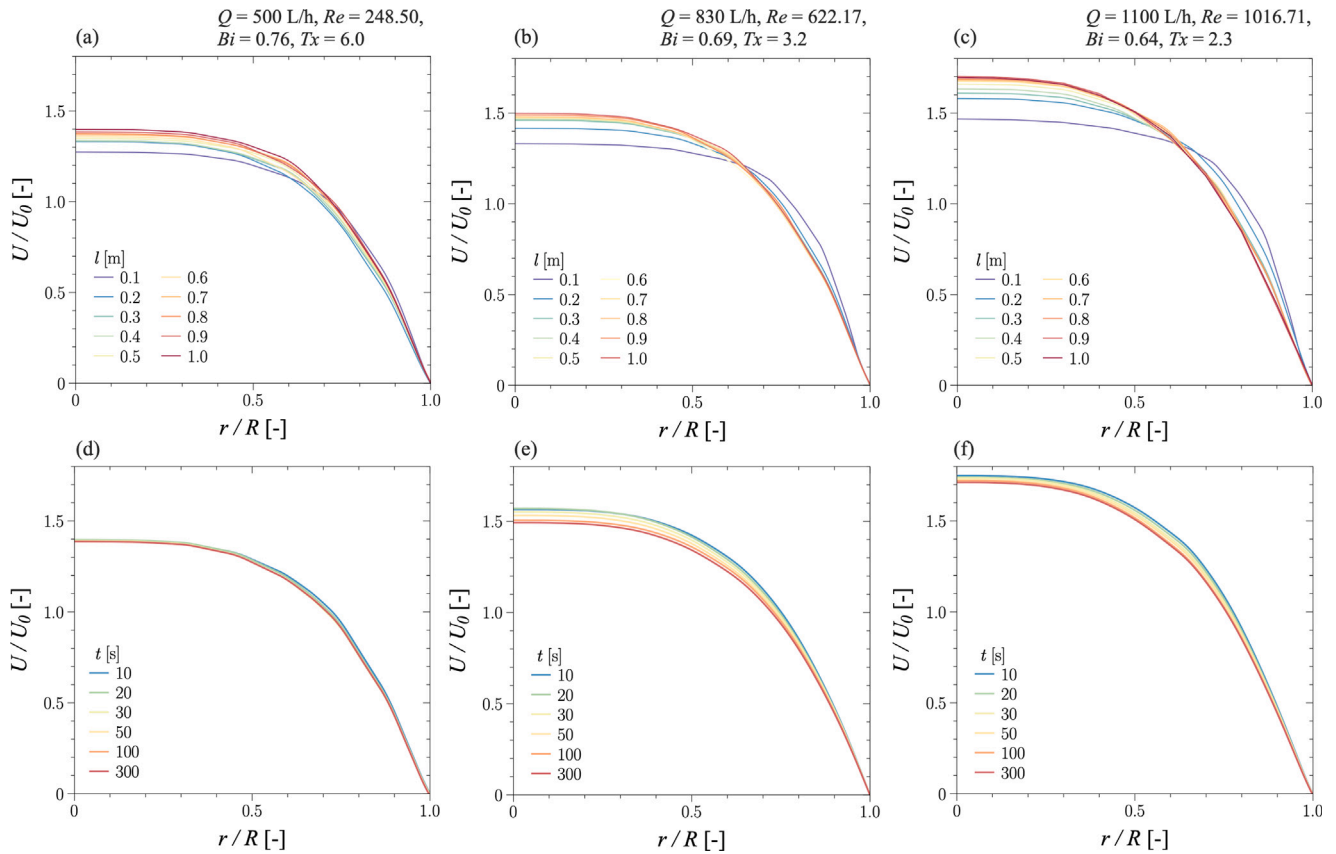


Fig. 5. Radial velocity profiles normalized by the maximum inlet velocity U_0 for different flow conditions. Subfigures (a-c) show the spatial development of velocity profiles along the pipe length at $t = 300$ s for three flow rates: (a) $Q = 500$ L/h ($Re = 248.50$, $Bi = 0.76$, $Tx = 6.0$), (b) $Q = 830$ L/h ($Re = 622.17$, $Bi = 0.69$, $Tx = 3.2$), and (c) $Q = 1100$ L/h ($Re = 1016.71$, $Bi = 0.64$, $Tx = 2.3$). Subfigures (d-f) present the temporal evolution of the velocity profiles at the pipe outlet ($x = 1$ m) for the same flow rates.

supplementary Structural Evolution Index (SEI), defined as the normalized rate of change of the structural parameter, is presented in the Supplementary Information (Fig. S3). The SEI quantifies the instantaneous rate of structural evolution, where higher values indicate more rapid structural change and lower values indicate approach to the quasi-steady state. The contour map highlights the faster structural stabilization at higher Reynolds numbers.

Overall, the CFD predictions using the Houska model capture the essential trends of pressure drop evolution with good accuracy. The relative error remains below 2% for most cases, as shown in Fig. 4(b). However, at high Reynolds numbers, the error increases to approximately 5% during the first 20–30 s. This discrepancy likely arises from the difficulty of capturing rapid structural breakdown dynamics with a single set of model parameters fitted from steady-state flow curves. Despite this limitation, the close agreement across a wide range of Re demonstrates that the Houska model is capable of reproducing both the steady-state and transient thixotropic behaviour of the system.

4.3.1. Simulated radial velocity profiles

Figs. 5(a-c) present the simulated radial velocity profiles, normalized by the maximum inlet velocity U_0 , along the pipe length at $t = 300$ s for three different flow rates. At the lowest flow rate ($Q = 500$ L/h, $Re = 248.50$, $Bi = 0.76$, $Tx = 6.0$), the velocity distribution is broad and nearly flat in the core, typical of plug-like flow. The axial velocity reaches about 1.4 times the inlet velocity, while variations in the high shear wall region remain small, Fig. 5(a). The relatively high Bi underscores the strong influence of yield stress, while the large Tx reflects substantial structural recovery, limiting structural breakdown along the pipe.

At the intermediate flow rate ($Q = 830$ L/h, $Re = 622.17$, $Bi = 0.69$, $Tx = 3.2$), the profiles develop more rapidly with distance downstream, Fig. 5(b). The axial velocity increases to roughly 1.5 times the inlet value, while the plug narrows and wall shear intensifies as yield stress effects weaken. At the highest flow rate ($Q = 1100$ L/h, $Re = 1016.71$, $Bi = 0.64$, $Tx = 2.3$), the velocity profiles approach a highly parabolic shape with a greatly reduced plug region, Fig. 5(c). Here, structural breakdown dominates, and yield stress and recovery effects play only a minor role compared to viscous and shear thinning contributions. Figs. 5(d-f) show the corresponding temporal evolution of velocity profiles at the pipe outlet ($x = 1$ m) over $t = 10 - 300$ s. At low flow rate (Fig. 5(d)), the profiles remain nearly unchanged with time, confirming that structural recovery dominates breakdown and maintains a stable plug-like flow. At intermediate flow rate (Fig. 5(e)), the core velocity gradually increases and curvature intensifies with time, reflecting progressive breakdown with only partial recovery. At the highest flow rate (Fig. 5(f)), temporal changes are more pronounced, wall gradients steepen continuously and the plug region further diminishes, driven by rapid structural breakdown and weak recovery. Velocity field development is governed by the combined effects of Re , Bi and Tx . High Bi and Tx stabilize plug-like profiles with minimal temporal evolution, while lower Bi and Tx , and higher Re accelerate structural breakdown, yielding more parabolic, shear thinning dominated profiles with pronounced spatial and temporal variations. These findings are consistent with the pressure-drop behaviour, where higher flow rates trigger faster structural breakdown.

4.3.2. Radial viscosity profiles

Fig. 6 shows the radial distributions of shear rate (solid lines) and viscosity (dashed lines) at different times for three different flow

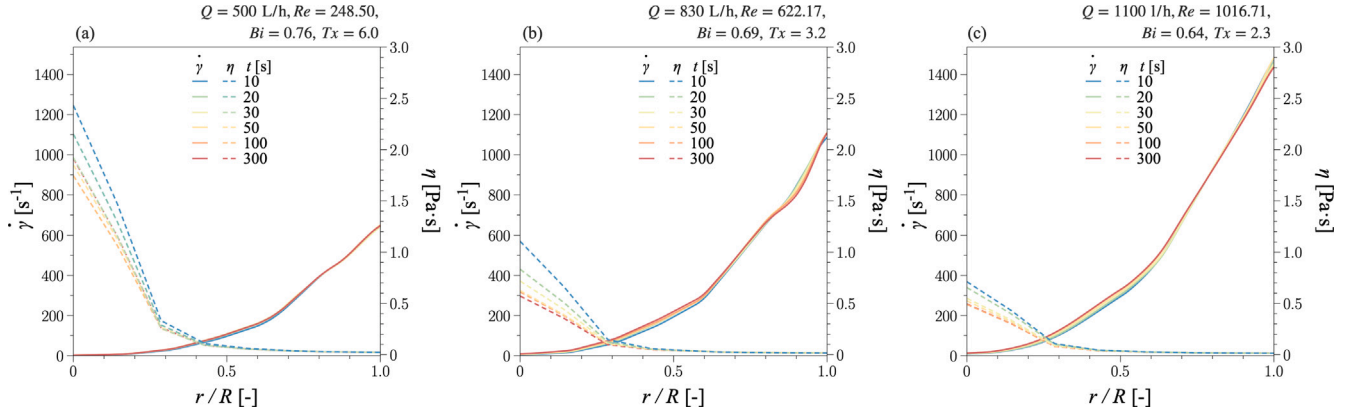


Fig. 6. Radial profiles of shear rate (solid lines) and viscosity (dashed lines) at different flow rates and times. (a) $Q = 500$ L/h ($Re = 248.50$, $Bi = 0.76$, $T_x = 6.0$), (b) $Q = 830$ L/h ($Re = 622.17$, $Bi = 0.69$, $T_x = 3.2$), and (c) $Q = 1100$ L/h ($Re = 1016.71$, $Bi = 0.64$, $T_x = 2.3$).

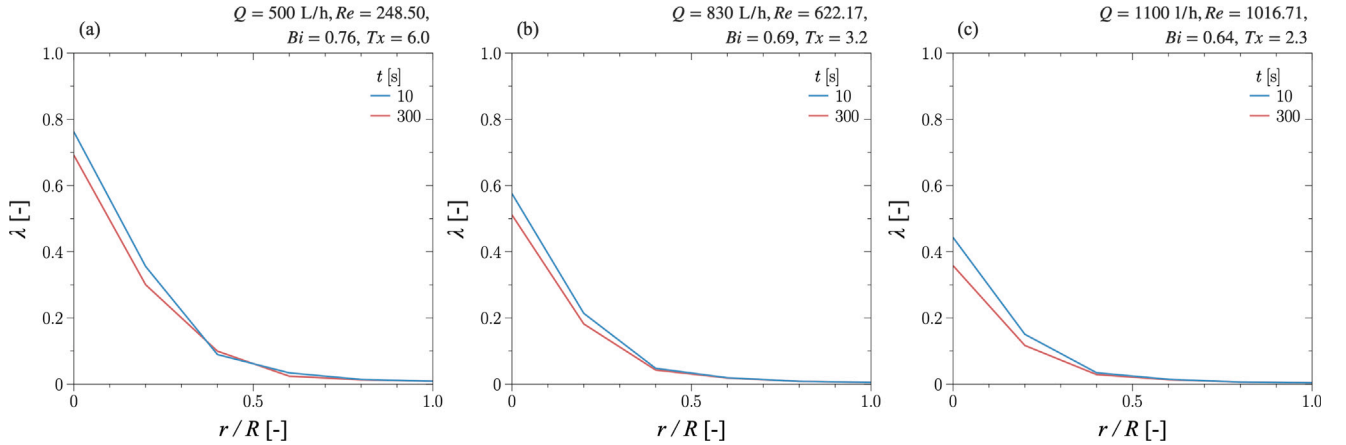


Fig. 7. Evolution of the structural parameter at different flow rates and times. (a) $Q = 500$ L/h ($Re = 248.50$, $Bi = 0.76$, $T_x = 6.0$), (b) $Q = 830$ L/h ($Re = 622.17$, $Bi = 0.69$, $T_x = 3.2$), and (c) $Q = 1100$ L/h ($Re = 1016.71$, $Bi = 0.64$, $T_x = 2.3$).

rates. As expected, shear rate increases with flow rate, while viscosity decreases. At the lowest flow rate ($Q = 500$ L/h, $Re = 248.50$, $Bi = 0.76$, $T_x = 6.0$), shear rates are low across the core and localized near the wall, while viscosity remains high in the plug region and decreases near the wall and with time. At the intermediate flow rate ($Q = 830$ L/h, $Re = 622.17$, $Bi = 0.69$, $T_x = 3.2$), shear rates near the wall increase markedly, narrowing the plug region. This is accompanied by a reduction in wall viscosity, while the core retains higher values. At the highest flow rate ($Q = 1100$ L/h, $Re = 1016.71$, $Bi = 0.64$, $T_x = 2.3$), shear rates are strongly localized at the wall from the onset, and viscosity decreases sharply in these regions. The plug region becomes progressively smaller, with the highest viscosity maintained only at the core where shear is lowest. Moreover, increasing the flow rate amplifies wall shear and accelerates viscosity reduction, while the fluid at the core experiences low shear and high viscosity.

4.3.3. Structural evolution

Fig. 7 shows the radial evolution of the structural parameter (λ) at two different times ($t = 10$ and 300 s) for three different flow rates: (a) $Q = 500$ L/h, (b) $Q = 830$ L/h, and (c) $Q = 1100$ L/h. The steady state structural parameter was determined by equating Eq. (11) to 0:

$$\lambda = \frac{1}{1 + \frac{k_b}{k_f} \left(\frac{\dot{\gamma}}{\dot{\gamma}_{ref}} \right)^{n_b - 1}} \quad (13)$$

where λ decreases from the pipe core towards the wall, reflecting the higher degree of structural breakdown under stronger shear near the

wall. At lower flow rate (Fig. 7(a)), the fluid retains a higher degree of structure in the core region, with ($\lambda \approx 0.7$) in the plug region. As the flow rate increases (Fig. 7 (b-c)), the viscosity at the core decreases, with λ reducing to below 0.5 at $Q = 1100$ L/h. Comparison of the two time snapshots indicates a temporal decrease in λ due to thixotropy, which is most pronounced in the core region. The associated T_x numbers demonstrate that higher flow rates correspond to lower apparent thixotropic recovery, consistent with lower structural relaxation under intensified shear conditions.

4.3.4. Yielded and unyielded regions

The yielding behaviour of the material was characterized using constant shear rate tests, wherein the transient shear stress evolves as a function of time under different imposed shear rates, as shown in Fig. 8. When the applied shear rate is greater than the critical value corresponding to the material's yield point, the internal structure progressively breaks down, resulting in a gradual decrease in stress until a steady state flow is reached. Conversely, when the applied shear rate is below the yielding threshold, the material remains predominantly unyielded, and structural recovery due to Brownian motion leads to an increase in stress with time. At intermediate shear rates near the critical value ($\dot{\gamma} \approx 10$ s⁻¹), the system exhibits a balance between structural breakdown and recovery, indicating the transition from solid-like to liquid-like behaviour. This behaviour is consistent with the typical thixotropic response of yield stress fluids, where the interplay between microstructural destruction and rebuilding governs the transient flow dynamics and determines the steady-state flow regime.

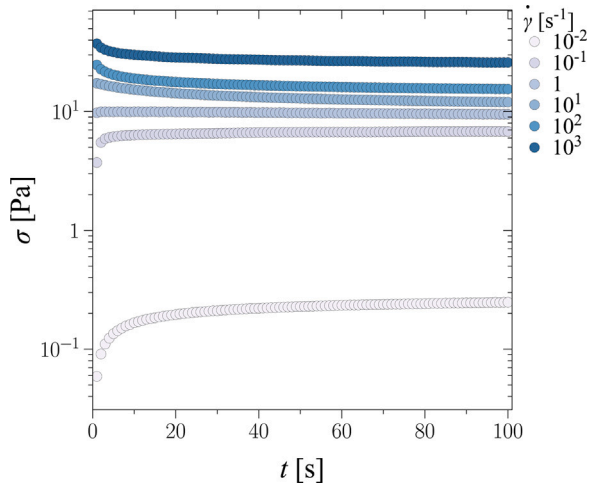


Fig. 8. Temporal evolution of the shear stress for several constant shear rates.

Using the identified critical shear rate as a threshold, the spatial distribution of yielded ($\dot{\gamma} \geq 10 \text{ s}^{-1}$) and unyielded ($\dot{\gamma} < 10 \text{ s}^{-1}$) regions in pipe flow was analysed, as illustrated in Fig. 9. The critical shear rate, obtained from the constant shear rate experiments, is used here as a practical indicator of the onset of yielding. Although yielding in thixotropic materials is fundamentally governed by the local stress and evolving structural state, this experimentally determined threshold provides a practical criterion for visualizing the transient evolution of the yielded and unyielded regions. At lower flow rates, a large unyielded plug persists near the axis, enclosed by a yielded annular region adjacent to the wall where the shear stresses are highest. As the flow rate increases, the yielded zone expands while the unyielded core diminishes and becomes unstable. At high flow rates $Q = 830 \text{ L/h}$ and $Q = 1100 \text{ L/h}$, the unyielded region separates into multiple smaller domains. This fragmentation suggests that intense local shear gradients and structural breakdown with time disrupt the plug integrity, causing intermittent yielding events within the core. Notably, this transition and fragmentation occur primarily within the entrance region of the pipe, where stress gradients are most pronounced and the flow is still developing. Further downstream, both yielded and unyielded regions stabilize and exhibit negligible temporal change, indicating that once the flow reaches a fully developed state, the spatial yielding pattern becomes steady and structurally equilibrated.

5. Neural network model for pressure drop prediction

5.1. Network design and architecture

A feed-forward fully-connected neural network (Multi-Layer Perceptron, MLP) was developed to predict the time-dependent pressure drop (ΔP) in a pipe as a function of time and flow rate. The objective of the model was to learn the nonlinear functional mapping

$$f_{\theta} : (t, Q) \rightarrow \Delta P, \quad (14)$$

where f_{θ} represents the neural network parameterized by weights and biases θ . The input layer consisted of two features, namely time and flow rate, while the output layer produced a single scalar value corresponding to the predicted pressure drop. The network comprised three hidden layers with neuron counts of 128, 128, and 64, respectively. Each hidden layer employed the Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and enable the network to represent complex relationships between flow conditions and pressure response. The output layer used a linear activation function to allow continuous valued predictions. The schematic architecture, shown in Fig. 10(a),

illustrates the two input neurons corresponding to time and flow rate, three fully connected hidden layers, and one linear output neuron representing $\Delta P(t, Q)$. The total number of trainable parameters was approximately 25217, distributed across four dense layers.

5.2. Training methodology

The model was trained using experimental and modelled (CFD) pressure drop data for constant flow rates ranging from 55 to 1100 L/h. Each flow rate dataset contained time resolved pressure values $\Delta P(t, Q)$, which were concatenated into a long format dataset of input-output pairs. Before training, all features were standardized using z-score normalization:

$$x' = \frac{x - \mu_x}{\sigma_x}, \quad y' = \frac{y - \mu_y}{\sigma_y}, \quad (15)$$

where μ and σ denote the mean and standard deviation of the training data. These parameters were stored and used consistently during prediction to maintain proper scaling of input vector (x') and target value (y'). The model was trained by minimizing the mean squared error (MSE) loss function:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^N \left[\Delta P_i^{\text{pred}}(t_i, Q_i) - \Delta P_i^{\text{exp/CFD}}(t_i, Q_i) \right]^2, \quad (16)$$

where $\Delta P_i^{\text{exp/CFD}}$ and ΔP_i^{pred} represent experimental/modelled and predicted pressure drops, respectively. The Adam optimizer was employed with a learning rate of 1×10^{-3} and a weight decay of 1×10^{-6} to regularize the model. Training was conducted using mini batches of 256 samples, and gradient clipping with a maximum norm of 1.0 was applied to stabilize convergence. An early stopping criterion with a patience of 120 epochs and tolerance of 1×10^{-6} was implemented to prevent overfitting. A validation set comprising 15% of the training data was used to monitor performance. The number of epochs to early stopping, mean absolute error (MAE), and root mean squared error (RMSE) were recorded to analyse convergence characteristics and training efficiency, Fig. 10(c). The network typically converged within 200–400 epochs, depending on the subset composition.

To determine the minimum experimental data required for accurate generalization, a combinatorial subset analysis was performed. For each value of k (number of training flow rates), all possible flow rate combinations were evaluated, and the subset yielding the lowest RMSE was selected. Fig. 10(b) presents a binary inclusion matrix showing which flow rates were included (orange) in the best performing subset at each k . The analysis revealed that low, mid, and high flow rate curves collectively provided the most balanced coverage of the dynamic range of pressure responses. The RMSE decreased sharply as k increased from 1 to 4 and plateaued thereafter, demonstrating that the network achieved reliable generalization with only a few representative datasets.

5.3. Prediction and model performance

After training, the neural network was used to predict $\Delta P(t)$ for all flow rates, including those not seen during training. Fig. 11(a–b) compares the predicted and experimental/modelled curves across the full flow rate range. The coloured points represent experimental/modelled data, and solid black lines represent model predictions. Note that the 20 different flow rates are split equally into two subplots for the sake of clarity.

The model accurately captured the temporal evolution of the pressure drop across all flow conditions, reproducing both the transient and steady-state regimes. Small deviations were observed at the beginning of the flow, likely due to high pressure drop gradients coupled with data sparsity and nonlinear edge effects. To assess quantitative accuracy, the percentage error was computed between predicted and experimental/modelled values. The overall error remained below 5% for all flow rates, confirming the model's robustness (Fig. 11 (c–d)).

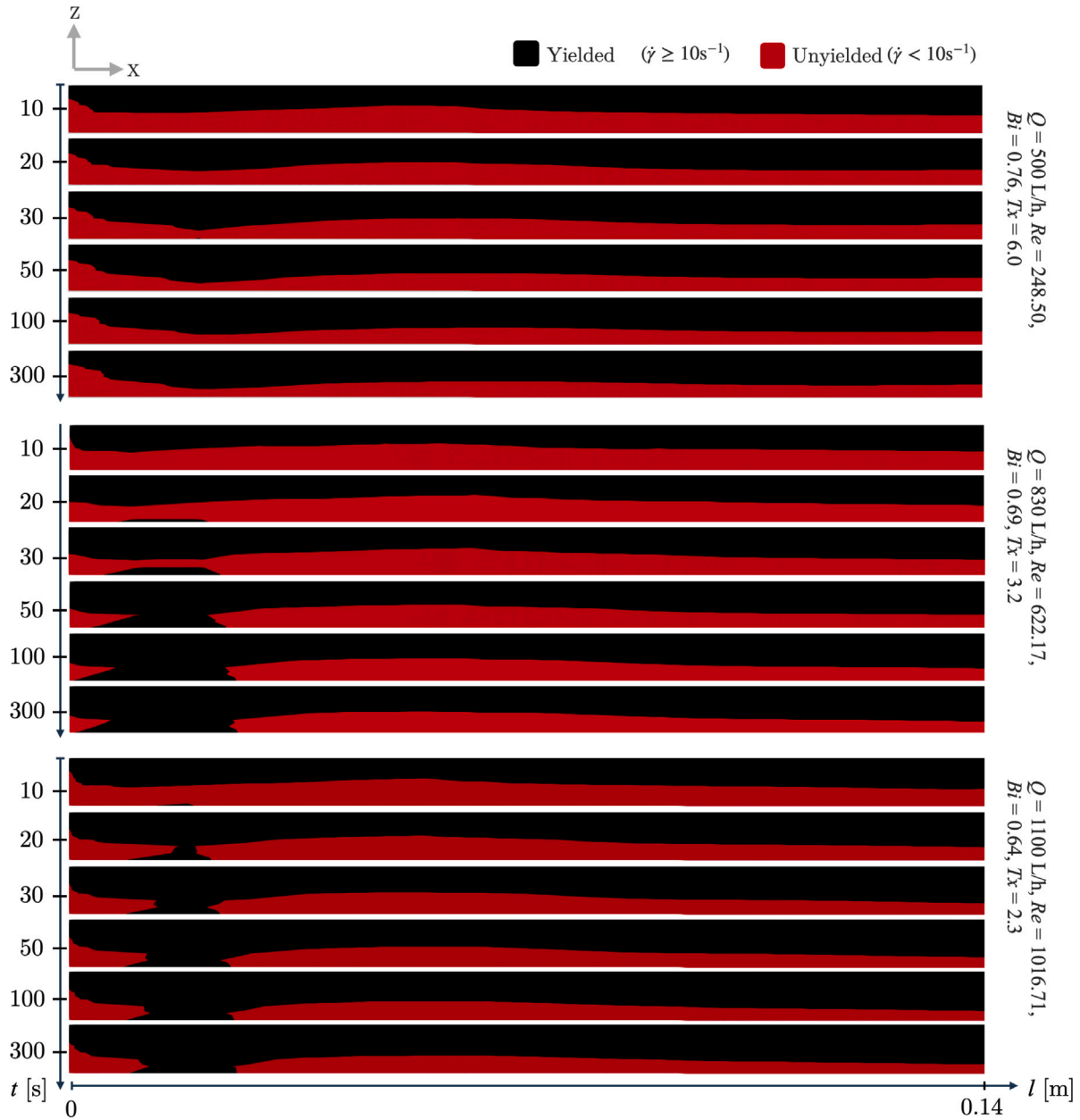


Fig. 9. Temporal evolution of yielded and unyielded regions in the pipe at three different flow rates.

The neural network provides a compact yet powerful framework for data-driven modelling of transient pressure response in pipe flow. Its architecture successfully captures the coupled dependence of ΔP on time and flow rate, and the error analysis demonstrates that three to four training datasets were sufficient for accurate generalization across the full flow rate range. This enables substantial reduction in experimental/modelling workload without compromising predictive performance. Additional validation and robustness analyses are presented in the Supplementary Information (Fig. S2). Benchmarking against Polynomial Ridge Regression, Gaussian Process Regression (GPR), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks showed that the proposed MLP achieves predictive performance comparable to the more complex recurrent architectures while substantially outperforming Polynomial Ridge Regression and GPR (Fig. S2(a,b)). The choice of a feed-forward MLP was motivated by the nature of the prediction task, where pressure drop is modelled directly as a function of time and flow rate, $f(t, Q) \rightarrow \Delta P$, with time explicitly provided as an input feature. Consequently, the problem is formulated as a

nonlinear regression task rather than a sequence-forecasting problem. The MLP model was able to accurately predict previously unseen flow rates with narrow 95% confidence intervals obtained from an ensemble of independently trained networks (Fig. S2(c)). Furthermore, the model remained robust to moderate levels of Gaussian noise introduced into the training data (Fig. S2(d)), with the RMSE remaining nearly constant for noise levels below 3%. Although the MLP possesses a larger number of trainable parameters than the alternative surrogate models (Fig. S2(e)), it provides accurate direct predictions without requiring previous pressure-drop states. Finally, despite being trained using pressure-drop data limited to the first 300 s of flow, the model successfully predicts the pressure-drop evolution up to 1000 s (Fig. S2(f)), demonstrating strong temporal generalization capability. Once trained (approximately 10–15 min), the feed-forward neural network generated transient pressure-drop predictions almost instantaneously, compared with the 7–11 h required for a single CFD simulation. This substantial reduction in computational time makes it well suited for

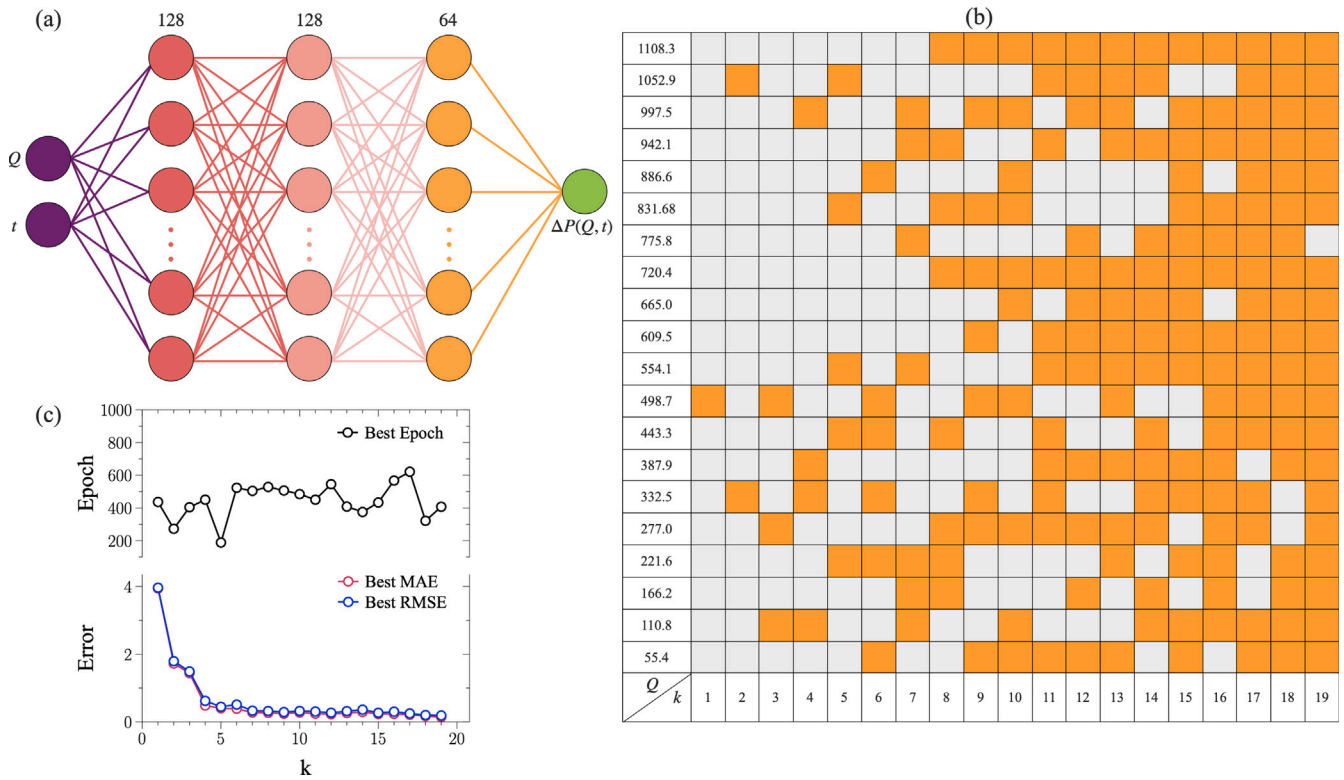


Fig. 10. (a) Schematic of the fully connected feed-forward neural network used for $\Delta P(t, Q)$ prediction, showing two inputs (t, Q), three hidden layers with ReLU activations, and a single linear output neuron. (b) Membership map of best performing training subsets at each number of training flow rates k , showing inclusion (orange) and exclusion (white) of individual datasets. (c) Early stopping epoch and error metrics (MAE, RMSE) as a function of k , indicating convergence behaviour and data efficiency.

engineering design optimization, parametric studies, digital-twin development, and online monitoring or control of industrial pipe-flow systems involving thixotropic fluids.

5.4. Limitations and future work

Laponite was selected as a well characterized model thixotropic fluid to establish and validate the proposed framework. However, industrial thixotropic materials often exhibit additional complexities, including viscoelasticity, multiphase behaviour, particle-size distributions, sedimentation, and more complex microstructural interactions. Extension of the proposed framework to such materials remain the subject of future work. CFD predictions rely on a phenomenological constitutive model in which the complex multiscale structural evolution of a thixotropic fluid is represented by a representative structural parameter. While the Houska model accurately reproduces the measured transient pressure drop behaviour, future developments will focus on multimodal and multiscale constitutive models that incorporate direct structural information alongside rheological measurements. Furthermore, the CFD prediction was validated for a single pipe geometry under laminar flow conditions. Although the reported Reynolds, Bingham, and thixotropy numbers facilitate comparison with other operating conditions and pipe diameters, further validation for different cross sections, diameters, geometries, and turbulent flow regimes is warranted. Finally, the proposed neural network surrogate was developed using experimental measurements together with validated CFD simulations and is intended to predict transient pressure drop evolution within the investigated range of operating conditions. Extending the surrogate to broader flow conditions, alternative physics informed models, and more diverse datasets, represents an important direction for future work.

6. Conclusions

This study integrated experiments, CFD simulations, and neural network modelling to examine the transient pipe flow behaviour of thixotropic yield-stress fluids. Experiments conducted using a custom-built pipe rig demonstrated a systematic decrease in pressure drop under constant flow rate, directly linked to the shear induced breakdown of the fluid's internal microstructure. CFD simulations employing the Houska constitutive model accurately reproduced the experimentally measured transient pressure-drop evolution, with relative errors below 5% for most flow conditions, and captured the dynamic balance between structural breakdown and recovery. The simulations further revealed that increasing flow rate reduces the size of the unyielded plug and promotes a transition from plug-like to shear thinning dominated flow, consistent with experimental observations. Analysis of the structural parameter showed that structural degradation is most pronounced near the pipe wall, while at high flow rates the central unyielded core becomes unstable and fragments before reaching a steady configuration further downstream. This behaviour highlights how local shear gradients and thixotropic kinetics govern the spatial evolution of yielded and unyielded regions during flow development. To reduce the computational effort, a feed-forward neural network trained on validated experimental and CFD data achieved 95% accuracy on unseen flow conditions while requiring only 4–5 representative pressure drop datasets for accurate prediction. Once trained, the surrogate generated predictions almost instantaneously, compared with 7–11 h required for a typical CFD simulation at a constant flow rate. Overall, the implemented neural network, trained on measured and CFD modelled pressure drop data, can predict transient pressure losses in model thixotropic pipe flow while substantially reducing experimental effort and computational cost, ideal for industrial process optimization and online flow monitoring. Extension of the proposed framework to other

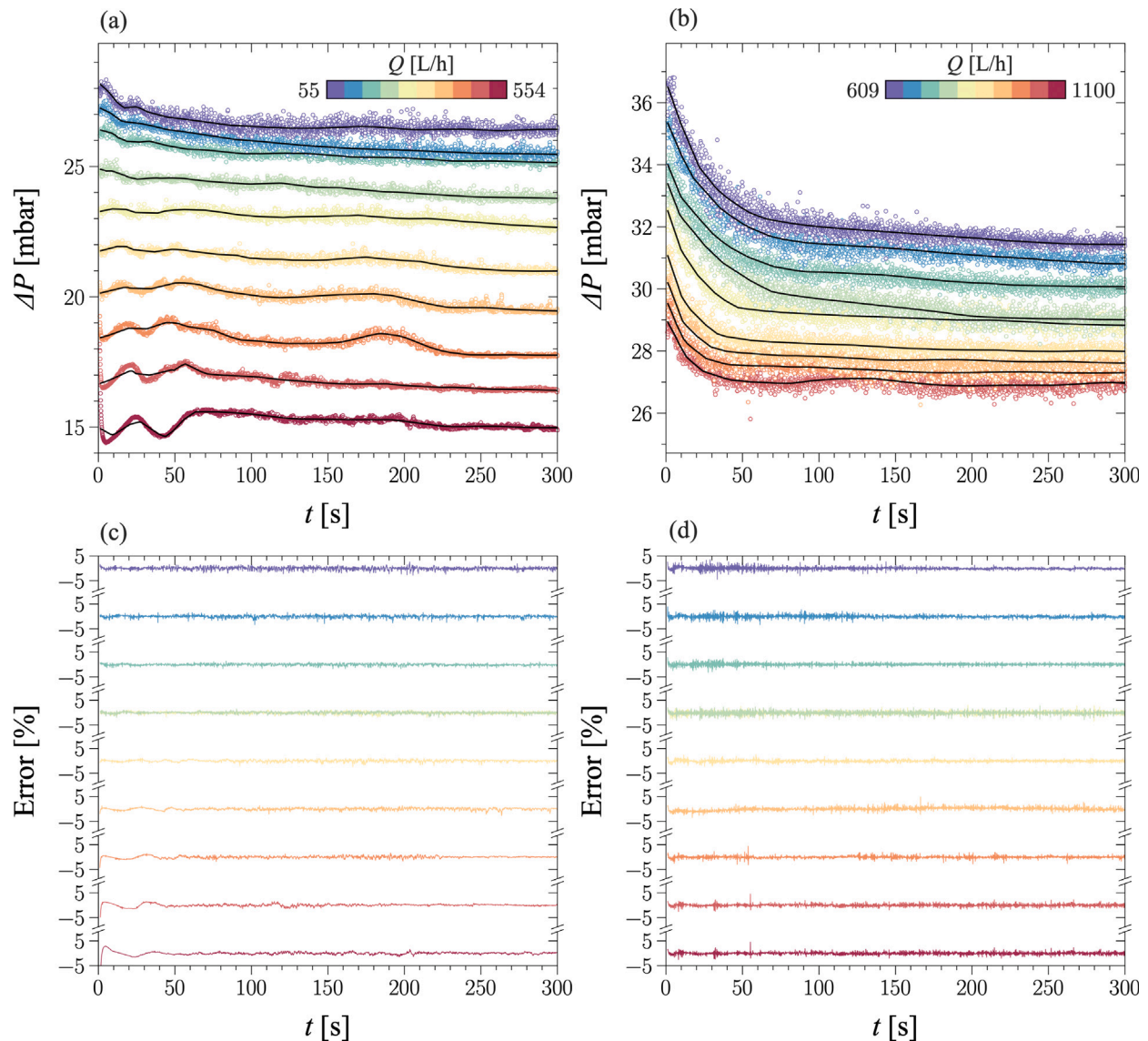


Fig. 11. Comparison of experimental/modelled and predicted pressure drop curves $\Delta P(t)$ for flow rates (a) 55–554 L/h, and (b) 609–1100 L/h. Coloured points denote experimental/modelled data, and solid black lines denote neural network predictions. The corresponding error is plotted in subfigures (c) $Q = 55$ –554 L/h, and (d) $Q = 609$ –1100 L/h.

fluids, geometries, and flow regimes remains an important direction for future work.

CRediT authorship contribution statement

Ases Akas Mishra: Writing – original draft, Methodology, Investigation. **Andreas Mark:** Writing – review & editing, Resources, Methodology. **Dragana Arlov:** Writing – review & editing, Resources, Methodology. **Roland Kádár:** Writing – review & editing, Resources, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.engappai.2026.116260>.

Data availability

Data will be made available on request.

References

- Ahmadpour, Ali, Sadeghy, Kayvan, 2013. An exact solution for laminar, unidirectional flow of houska thixotropic fluids in a circular pipe. *J. Non-Newton. Fluid Mech.* 194, 23–31.

- Ahmed, Faizan, Mohammed, Nayeemuddin, Mewada, Hiren, Aziz, Mohd Sharizal Abdul Khor, CY, 2026. An experimental evaluation, performance analysis, and improvement of water desalination system using optimized machine learning. *Process. Integr. Optim. Sustain.* 10 (2), 737–752.
- Amini, Kasra, Mishra, Ases Akas, Sivakumar, Amit Kumar, Arlov, Dragana, Innings, Fredrik, Kádár, Roland, Tammisola, Outi, Lundell, Fredrik, 2024. Scaling laws for near-wall flows of thixo-elasto-viscoplastic fluids in a millifluidic channel. *Phys. Fluids* 36 (2).
- Barnes, Howard A., 1997. Thixotropy—a review. *J. Non-Newton. Fluid Mech.* 70 (1–2), 1–33.
- Bartholomew, Paul, Denner, Fabian, Abdol-Azis, Mohd Hazmil, Marquis, Andrew, van Wachem, Berend G.M., 2018. Unified formulation of the momentum-weighted interpolation for collocated variable arrangements. *J. Comput. Phys.* 375, 177–208.
- Croudace, Andrew I., Pritchard, David, Wilson, Stephen K., 2017. Unsteady flow of a thixotropic fluid in a slowly varying pipe. *Phys. Fluids* 29 (8).
- Doormaal, J.P. Van, Raithby, G.D., 1984. Enhancements of the simple method for predicting incompressible fluid flows. *Numer. Heat Transfer* 7 (2), 147–163.
- Escudier, M.P., Presti, F., 1996. Pipe flow of a thixotropic liquid. *J. Non-Newton. Fluid Mech.* 62 (2–3), 291–306.
- Hussain, Mohib, Lin, Du, Waqas, Hassan, Ali, Bagh, Shah, Nehad Ali, 2025. Machine learning-integrated computational analysis on a blood-based ternary nanofluid flow in a stenosed artery with the artificial neural networks and modified finite difference approach. *Chaos Solitons Fractals* 199, 116626.
- Ingelsten, Simon, Mark, Andreas, Edelvik, Fredrik, 2019. A Lagrangian-Eulerian framework for simulation of transient viscoelastic fluid flow. *J. Non-Newton. Fluid Mech.* 266, 20–32.
- Ingelsten, Simon, Mark, Andreas, Jareteg, Klas, Kádár, Roland, Edelvik, Fredrik, 2020. Computationally efficient viscoelastic flow simulation using a Lagrangian-Eulerian method and GPU-acceleration. *J. Non-Newton. Fluid Mech.* 279, 104264.
- Kumar, Maddina Dinesh, Raju, CSK, Sajjan, Kiran, Dharmiah, Gurram, Shah, Nehad Ali, Yook, Se-Jin, 2025. Deep neural network-based prediction and computational fluid dynamics analysis of convective heat transfer in dusty fluid flow over heated surface. *Phys. Fluids* 37 (2).
- Mahmoudabadbozchelou, Mohammadamin, Kamani, Krutarth M, Rogers, Simon A, Jamali, Safa, 2022. Digital rheometer twins: Learning the hidden rheology of complex fluids through rheology-informed graph neural networks. *Proc. Natl. Acad. Sci.* 119 (20), e2202234119.
- Mark, A., Rundqvist, R., Edelvik, F., 2011. Comparison between different immersed boundary conditions for simulation of complex fluid flows. *Fluid Dyn. Mater. Process.* 7 (3), 241–258.
- Mark, Andreas, van Wachem, Berend G.M., 2008. Derivation and validation of a novel implicit second-order accurate immersed boundary method. *J. Comput. Phys.* 227 (13), 6660–6680.
- Mark, Andreas, et al., 2025. IPS iboflow. <https://industrialpathsolutions.com/ips-iboflow>.
- Mewis, Jan, Wagner, Norman J., 2009. Thixotropy. *Adv. Colloid Interface Sci.* 147, 214–227.
- Mishra, Ases Akas, Almhöjd, Ulrica, Çevik-Aras, Hülya, Fistic, Amela, Olofsson, Richard, Almståhl, Annica, Kádár, Roland, 2025a. The complex shear time response of saliva in healthy individuals. *Phys. Fluids* 37 (1).
- Mishra, Ases Akas, Ghai, Viney, Matovic, Valentina, Arlov, Dragana, Kádár, Roland, 2025b. One test to predict them all: Rheological characterization of complex fluids via artificial neural network. *Eng. Appl. Artif. Intell.* 139, 109598.
- Mohammed, Nayeemuddin, Ahmed, Faizan, Mewada, Hiren, 2026. Machine learning modeling and experimental optimization of heat exchanger for efficient building systems. *J. Appl. Comput. Mech.* e19588.
- Mohammed, Nayeemuddin, Ahmed, Faizan, Mewada, Hiren, Rathod, Rajshekhar G, Sonawane, Sagar K, 2025. Experimental and machine learning optimization of centrifugal pump performance. *Flow Meas. Instrum.* 103048.
- Nahavandian, M.H., Pourjafar, M., Sadeghy, K., 2018. Stability of thixotropic fluids in pipe flow. *Sci. Iran. Trans. B: Mech. Eng.*
- Olusola, Olufolahanmi, Nguyen, Tan, Saasen, Arild, Al-Safran, Eissa, 2025. Prediction of Frictional Pressure Losses for Time Dependent Drilling Fluids in Pipe Flow. Technical Report, Tetra Technologies Inc.; New Mexico Institute of Mining and Technology; Det norske oljeselskap / University of Stavanger; Kuwait University.
- Pereira, Américo S., Pinho, Fernando T., 2001. Recirculating turbulent flows of thixotropic fluids. In: ASME International Mechanical Engineering Congress and Exposition, vol. 35685, American Society of Mechanical Engineers, pp. 111–123.
- Pritchard, David, Croudace, Andrew I., Wilson, Stephen K., 2020. Thixotropic pumping in a cylindrical pipe. *Phys. Rev. Fluids* 5 (1), 013303.
- Saadat, Milad, Mangal, Deepak, Jamali, Safa, 2023. A rheologist's guideline to data-driven recovery of complex fluids' parameters from constitutive models. *Digit. Discov.* 2 (4), 915–928.
- Wang, Jian, Masood, Khalid, Shah, Nehad Ali, et al., 2025. Artificial neural networks analysis of magneto-boundary layer flow of partially ionized Prandtl tri-hybrid nanofluid with entropy generation over heated cylinder. *Chaos Solitons Fractals* 199, 116808.
- Yan, Huaixiao, Ding, Jiannan, Tao, Chengcheng, 2025. A physics-informed neural network solution for rheological modeling of cement slurries. *Fluids* 10 (7), 184.
- Yousuf, Noman, Lester, Daniel, Rudman, Murray, Dentz, Marco, Eshtiaghi, Nicky, 2025. Turbulent pipe flow of thixotropic fluids. *J. Fluid Mech.* 1011, A45.
- Zhang, Tianjie, Wang, Donglei, Lu, Yang, 2025. A Navier–Stokes-informed neural network for simulating the flow behavior of flowable cement paste in 3D concrete printing. *Buildings* 15 (2), 275.
- Zhang, Lianfu, Wang, Hongjiang, Wu, Aixiang, Yang, Ke, Kong, Peng, 2023. Simulation of circular pipe flow of thixotropic cemented tailings pastes. *Chem. Eng. Res. Des.* 196, 671–684.