



Original Article

A hybrid modeling approach for predicting non-Newtonian flow through multilayer sintered composite-cloths

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ABSTRACT

The accurate determination of pressure loss across filter media is of central importance in the design of filtration processes, as it directly affects energy efficiency and thus operating costs. While Darcy-based approaches reliably describe the flow of Newtonian fluids, no transferable models exist for non-Newtonian fluids flowing through multilayer sintered metal wire composite-cloths, despite their widespread use in industrial applications such as polymer melt filtration or heavy fuel oil filtration in marine engines. To address this gap, this study develops and systematically compares several modeling approaches for predicting the flow velocity of shear-thinning fluids through such composite-cloths, relying on quantities available in industrial practice, such as standardized air permeability measurements. The investigated approaches comprise a physics-based white box model derived from a modified Darcy law, a purely data-driven black box model based on gradient boosting, including a target-scaled variant, and hybrid models combining both paradigms in serial and parallel configuration. All models are evaluated across ten random data splits and compared using paired statistical tests. The hybrid structures outperform the purely data-driven model, with the parallel configuration achieving the lowest error at a mean MAPE of $5.59 \pm 1.85\%$. The reported performance reflects interpolation within the investigated parameter space of three cloth types, six pore sizes, and three silicone oils. Overall, the proposed hybrid modeling framework provides a viable method for predicting the flow velocity of non-Newtonian fluids in multilayer sintered metal wire composite-cloths.

1. Introduction

Metal wire cloths are widely used in specialized industrial applications, particularly under extreme operating conditions such as high temperatures and severe mechanical loads (Azizi, 2019). Typical fields of application include the filtration of heavy fuel oils in marine engines to prevent engine damage, the filtration of polymer melts during extrusion processes to ensure high product quality, and the use of composite-cloths as retaining elements for the stationary phase in chromatographic columns (Carley and Smith, 1978; Markarian, 2008; Onishchenko et al., 2023; Savins, 1969). In all these applications, the filter medium represents a central functional component of the process and largely determines its performance and economic efficiency. A key parameter in the selection of suitable filter media is the permeability, particularly in sieve filtration applications (Ångeslevä et al., 2024; Azizi, 2019; Purchas and Sutherland, 2002). According to the current state of the art, permeability is commonly characterized using standardized air

permeability measurements. In such tests, the volumetric air flow rate passing through a defined filter area at a specified pressure drop is determined. This measurement serves as a practical reference for evaluating and comparing different filter media. For the flow of Newtonian fluids through porous media, permeability can be related to the superficial velocity as a function of pressure loss using Darcy's law (Darcy, 1856). In industrial applications, the pressure loss generated during flow is of particular importance, as it directly affects operating costs and thus represents a key parameter in process design. An appropriate balance must therefore be achieved between separation efficiency and economic feasibility (Azizi, 2019). While well-established physical descriptions exist for the flow through single layer media with Newtonian fluids, no generally accepted modeling approach is available for the flow of non-Newtonian fluids through porous metal wire composite-cloths.

The modeling of non-Newtonian fluid flow through porous media has been the subject of research for several decades. Sadowski and Bird (1965) incorporated the Ellis model into Darcy's equation to describe

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flow through packed beds. However, this approach requires an empirical correction factor to fit the model to experimental data. Early work on non-Newtonian filtration focused primarily on cake-forming processes. Shirato et al. (1980) developed a theory for the constant-pressure filtration of power-law fluids that accounts for compressible filter cakes, whereas the flow through the clean filter medium itself was not addressed. A rigorous mathematical treatment of this latter problem was provided by Bourgeat et al. (2001), who derived a homogenized macroscopic law for the flow of Carreau fluids through thin periodic filters and validated it numerically against the underlying microscopic model, motivated by the observation that the pressure drop across a filter differs substantially from both the Newtonian case and the corresponding unobstructed non-Newtonian flow. For the specific case of metal wire cloths, Sun et al. (2015) combined experiments and numerical simulations to derive a correlation for the pressure drop across wire mesh filters as a function of structural parameters, albeit limited to Newtonian air flow, the same configuration underlying standardized air permeability measurements. Eberhard et al. (2019) proposed an approach for packed beds in which the pore space is approximated by a single cylindrical capillary with a characteristic radius. By calculating the velocity profile within the capillary, an effective mean viscosity is derived without introducing empirical correction factors. However, the validation of this model is limited to idealized beds consisting of monodisperse spheres, restricting its applicability to real porous media with complex geometries. For filter cloths, Pachner et al. (2019) developed a coupled model combining CFD simulations with heuristic methods to describe the pressure loss of single-layer square weave and dutch weave wire cloths during polymer melt filtration. More recently, Bennett et al. (2024) developed and experimentally validated a CFD methodology for predicting the pressure drop across multi-layered woven screens for polymer melts, showing that the downstream support layers must be explicitly accounted for, and extended this approach to the simulation of complete industrial filter systems including filter blocking (Bennett et al., 2025). These CFD-based approaches, however, require detailed geometric resolution of the weave structure and considerable computational effort, which limits their applicability for the rapid screening of filter media in industrial practice.

In parallel, machine learning methods have increasingly been applied to the modeling of non-Newtonian fluids. Reyes et al. (2021) employed physics-informed neural networks (PINNs) to learn the effective viscosity of generalized Newtonian fluids directly from velocity and pressure measurements, and Mahmoudabadbozchelou et al. (2022) extended this concept to a broad class of complex fluid constitutive models with their non-Newtonian PINN framework. Tree-based ensemble methods such as gradient boosting have likewise proven effective for regression tasks involving non-Newtonian flows (Tizakast et al., 2023). Beyond flow prediction, data-driven methods have also been used to infer quantities that are difficult to measure directly. Pahari et al. (2021) estimated microstructural properties of wormlike micelles, otherwise only accessible via small-angle neutron scattering, from standard macroscopic rheology measurements using batch Bayesian optimization. While these studies demonstrate the potential of data-driven rheological modeling, they are not directly transferable to the present application. PINN-based approaches require spatially resolved field data and explicit formulation of the governing equations. The mesoscopic framework of Pahari et al. (2021) in turn, addresses the microstructural characterization of wormlike micellar systems rather than the prediction of flow through porous media. The approach pursued in this work therefore relies exclusively on quantities obtainable with standard industrial measurement techniques. To date, no robust modeling approach exists for multilayer sintered metal wire composite-cloths that relies solely on such practically accessible inputs.

Against this background, a hybrid modeling approach appears particularly suitable for closing this gap. Hybrid models (HBM) combine mechanistic white box models (WBM), such as first-principles or phenomenological models, with purely data-driven black box models

(Chen and Ierapetritou, 2020; Thompson and Kramer, 1994; Zhai et al., 2024). In recent years, the use of hybrid models has increased significantly due to advances in computational power, improved algorithms, and the growing complexity of industrial processes. A central advantage of hybrid models lies in the structural integration of physical prior knowledge, which constrains the hypothesis space and reduces the required amount of training data. At the same time, the mechanistic component acts as a regularizing element, decreasing susceptibility to overfitting compared to purely data-driven approaches. The combination of both modeling paradigms further enables the representation of complex nonlinear effects that are difficult to capture using mechanistic formulations alone.

This study presents and systematically compares different modeling approaches for predicting the flow velocity of non-Newtonian fluids through multilayer sintered metal wire composite-cloths. These are a physics-based white box model, a purely data-driven black box model including a target-scaled variant, and hybrid models in both serial and parallel configuration. All models are based on standardized air permeability measurements as well as the rheological parameters of the fluid. The remainder of this paper is organized as follows: Section 2.1 introduces the investigated composite-cloths and their structural properties, followed by a description of the experimental setup in Section 2.2 and the measurements of the fluid properties in Section 2.3. Section 2.4 describes the dataset and its preparation, including the group-based train-test split and the logarithmic transformation of the target variable, and subsequently introduces the developed models: the physics-based white box model, a purely data-driven black box model with a target-scaled variant, and two hybrid models in serial and parallel configuration, together with the training and hyperparameter optimization procedure of the data-driven components. Section 3 evaluates the predictive performance of all model variants on unseen test data, statistically compares the different architectures, and analyzes the contribution of the physical prior knowledge. Finally, Section 4 summarizes the main findings and outlines directions for future work.

2. Material and methods

2.1. Composite-cloths

The present study uses metal composite-cloths listed in Table 1 from Spörl KG (Sigmaringendorf, Germany). These consist of three to five distinct wire cloth layers that have been sintered together.

The schematic structure of the composite-cloths is illustrated in Fig. 1. The cloth A configuration comprises a total of three layers. The first layer is the upper filtration layer, and the second and third layers are the inner and outer support structures, respectively. The latter are composed of square weave cloth. The filtration layer with the smallest pore size is primarily responsible for separation performance, thereby determining the fineness of the composite-cloth. The support structure guarantees the mechanical and form stability of the composite-cloth. The cloth B configuration consists likewise of two support structures made of square weave cloth to provide mechanical stability. A drainage layer is positioned on top of the support structure, with the filtration layer positioned on top of the drainage layer. Ultimately, a protective layer of square weave cloth is present to prevent damage to the filtration

Table 1
Characteristics of the used composite-cloths.

Composite-cloth	Number of layers	Geometric pore size in μm	Composite thickness in mm	Porosity ^a in %
Cloth A	3	5–15	2.0	60
Cloth B	5	5–15	2.4	55
Cloth C	5	5–15	1.7	30

^a Ratio of the cloths open area to its total volume is calculated using the cloths external dimensions: thickness, width, and thickness.



Fig. 1. Schematic structure of the composite-cloths used. The composite-cloths consist of different stacked layers that are sintered together.

layer from mechanical causes. As with cloth B, cloth C comprises a filter layer surrounded by a drainage layer and a protective layer of square weave cloth. The support structure of cloth C, on the other hand, consists of two plain dutch weaves, offset by 90° to each other. The dataset used for modeling comprises these three composite-cloths, each featuring six distinct filter finenesses: 5, 7, 8, 10, 12 and 15 μm . These finenesses correspond to the standard range in which this type of composite-cloth is commercially manufactured, ensuring the practical relevance of the investigated media. The filtration layer consists of Betamesh-PLUS wire cloth. This special weave ensures high flow rates with minimal pressure loss.

2.2. Experimental procedure

The dataset employed for the data-driven modeling comprises experimental data that was generated during flow-through tests on a standard pressure filter cell. The experimental setup consists of a cylindrical pressure cell with a volume of 300 ml. The filter cloth, with a filter area of 19.63 cm^2 , is installed beneath the cylinder. The diameter of the filter area corresponds to that of the pressure chamber. Compressed air was used to press the fluid through the composite-cloth at a constant pressure. The mass flow rate was recorded gravimetrically using a laboratory scale. During this study, 250 g of fluid was filled into the pressure cell for each experiment. The initial point of evaluation was determined subsequent to the detection of 20 g of fluid, with the objective of filtering out any impulses that may have been detected on the scale. At the start of the experiment, the hydrostatic pressure with the pressure cell filled is 0.012 bar. Because the gravimetrically recorded fluid mass increased linearly over time, the hydrostatic pressure was neglected. All flow tests were performed in triplicate. The dataset used for modeling consists of the averaged values.

2.3. Fluid properties

Various viscosities of linear silicone oils (Optimal Products, Bad Oeynhausen, Germany) were used for the flow tests. Fig. 2 shows the measured apparent viscosities η plotted against the shear rate $\dot{\gamma}$. Up to a shear rate of 1000 s^{-1} , the measurements were performed using a HAAKE™ MARS™ Rheometer (Thermo Scientific, Karlsruhe, Germany). Measurements at higher shear rates were performed using a self-assembled, piston-driven capillary rheometer. Samples were forced to flow through a 0.5 mm diameter, 20 mm long stainless steel capillary at controlled volumetric flow rates corresponding to constant shear rate values using a 20 mm diameter piston. Both rheometers were actively temperature-controlled to prevent a temperature rise due to viscous dissipation. All measurements were conducted at 20 °C.

The measurement results show that the silicone oils examined exhibit linear, Newtonian flow behavior at low stress levels. Within this range, viscosity is shear-rate independent and corresponds to the zero-shear viscosity η_0 . As the shear rate increases, however, the viscosity

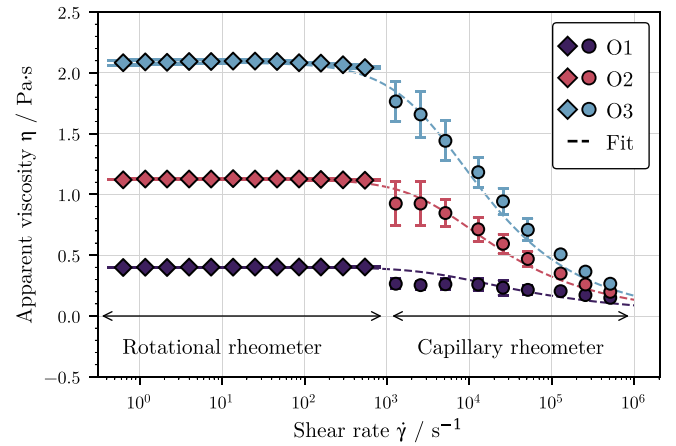


Fig. 2. Measured apparent viscosity plotted as a function of shear rate for the silicone oils used along with fits using the Carreau-Yasuda model.

decreases. The silicone oils exhibit shear-thinning behavior. The overall flow behavior can be described using the Carreau model (Gan, 2012) as follows:

$$\eta(\dot{\gamma}) = \left(\eta_{\infty} + (\eta_0 - \eta_{\infty}) (1 + (\lambda \dot{\gamma})^2)^{\frac{n-1}{2}} \right) \quad (1)$$

Here, n is the power law exponent in the shear-thinning range, η_{∞} represents the limiting shear viscosity at high shear rates and λ is a characteristic time constant that determines the transition from Newtonian to shear-thinning behavior. As the Carreau model only represents the transition range between zero-shear viscosity and the power law to a limited extent, Yasuda et al. (1981) expanded the model to include the additional parameter α , which controls the width and shape of the transition range. It enables a more accurate fit to experimental data. This is particularly advantageous when the transition between the two flow regimes is not abrupt, but rather occurs over a broad or asymmetric range. The resulting Carreau-Yasuda model is as follows:

$$\eta(\dot{\gamma}) = \left(\eta_{\infty} + (\eta_0 - \eta_{\infty}) (1 + (\lambda \dot{\gamma})^{\alpha})^{\frac{n-1}{\alpha}} \right) \quad (2)$$

Table 2

Material properties of the silicone oils used, along with the Carreau-Yasuda model parameters and corresponding coefficients of determination.

Silicone oil	ρ kg·m ⁻³	η_0 Pa·s	η_{∞} Pa·s	λ s	n	α	R ²
O1	970	0.40	2.00e-15	2.2e-4	0.718	1.160	0.79
O2	970	1.12	2.39e-15	2.4e-4	0.611	1.158	0.98
O3	970	2.08	2.51e-15	2.7e-4	0.549	1.053	0.99

Table 2 lists the material properties of the silicone oils used in this study, as well as the parameters determined by adapting them to the Carreau-Yasuda model.

2.4. Model development

This section first describes the dataset and its preparation. Subsequently, the models developed in this study are presented, starting with the physics-based white box model (WBM). Next, a purely data-driven black box model (BBM) is introduced, followed by a variant of the BBM with feature-based target scaling. Finally, two hybrid models (HBM) combining the WBM with the BBM are described, which differ in their architecture: a serial and a parallel configuration.

2.4.1. Dataset and data preparation

Initially, the dataset was prepared for the training and evaluation process. The dataset for this study comprises a total of 525 data points.

Table 3 presents the structure of the dataset, along with the selection of the six features and the target variable. A data point with index i is defined as the values $X_{i,f}$ of feature f and the associated target variable y_i . The features selected for this study include the pressure loss Δp , the resistance of the filter cloth R_m , the thickness of the filter cloth L , the geometric pore size d_p , the zero-shear viscosity of the fluid η_0 , and the characteristic time constant λ from the Carreau-Yasuda model. Since all features are numerical quantities, encoding is not necessary. Likewise, the features were not scaled, as this is not an essential step for tree-based models.

Model training began by splitting the dataset into a training and test set. To prevent data leakage between the two datasets, the data points were first assigned to groups and the split was then performed in a stratified manner. In total, the data points were divided into 54 groups based on cloth thickness, geometric pore size, and zero-shear viscosity of the fluids. For the group-wise train-test split, the features L and η_0 served as stratification criteria. Subsequently, 25% of the groups were randomly assigned to the test set, while the remaining data points constitute the training set, comprising 40 groups with a total of 391 data points. The resulting division of the dataset is illustrated in Fig. 3.

To ensure reproducibility and to account for the influence of random effects, all pipelines described in the following were executed with ten different random seeds (0–9). These seeds were applied consistently to all random processes, including the train-test split, model training, and hyperparameter optimization.

Beyond the partitioning of the dataset, the target variable y_i itself required preprocessing. As illustrated in Fig. 3, its distribution is strongly right-skewed, spanning several orders of magnitude. To mitigate this skewness, a logarithmic transformation was applied, yielding the transformed target variable z_i as follows:

$$z_i = \ln(y_i) \quad (3)$$

Since the model is trained in logarithmic space, its predictions correspond to the conditional mean of the log-transformed target rather than the conditional mean of the original scale. Due to the nonlinearity of the exponential transformation, directly exponentiating these predictions systematically underestimates the expected value in the original space. For this reason, the back-transformation of the forecast values $\hat{z}_i$ to the original space was performed, using a bias correction factor

according to Baskerville (1972), as shown in Eq. (4).

$$\hat{y}_i = e^{(\hat{z}_i + 0.5 \cdot \sigma^2)} \quad (4)$$

In this context, the symbol σ^2 denotes the variance of the residuals in the logarithmic target space. The residuals were obtained via stratified group 5-fold cross-validation on the training dataset, following the same grouping and stratification scheme as described above for the train-test split. In each fold, the model was trained on the remaining folds and used to predict the log-transformed target values of the observations in the held-out validation fold. Since each prediction was thus generated by a model that had not been trained on the respective observation, these predictions constitute out-of-fold estimates. The residuals were calculated as the difference between the observed log-transformed target values and their out-of-fold predictions, ensuring that they reflect the model's out-of-sample error rather than the optimistically biased in-sample error.

To verify the assumptions underlying the bias correction, the distribution of the pooled out-of-fold log-space residuals used to estimate σ^2 was examined for all three model types and all ten seeds. The corresponding diagnostic plots are provided in Table A.5–8, and the distributional statistics for each seed are provided in Table A.1–4 in Appendix A. Table 4 summarizes the sample skewness and excess kurtosis averaged over all seeds.

For the BBM, the residuals are with a skewness of -0.11 ± 0.55 approximately symmetric with a slightly positive mean excess kurtosis, indicating a distribution close to normal with marginally heavier tails in individual seeds. The BBM with feature-based target scaling shows a moderate negative skewness, a left-skewed residual distribution with occasional larger negative residuals, while its mean excess kurtosis remains close to zero. The HBM exhibits the most symmetric residuals and a consistently negative excess kurtosis, corresponding to a slightly platykurtic distribution with lighter-than-Gaussian tails. Overall, the deviations from normality are moderate for all model types, and the residuals are approximately symmetric and show no pronounced heavy tails. Since the bias correction according to Eq. (4) is primarily sensitive to strong skewness and heavy tails, these deviations do not compromise its applicability.

The detailed architecture of the individual model types and their corresponding pipelines is described in the following sections. The effect of the logarithmic transformation on the prediction quality is discussed in the results section. The logarithmic transformation is applied identically to all models.

2.4.2. White box sub-model

Darcy's law (Darcy, 1856) describes the apparent velocity v of a fluid with a dynamic viscosity η within a porous medium of thickness L at a pressure gradient Δp as follows:

$$v = \frac{\Delta p}{R_m L \eta} \quad (5)$$

The resistance value R_m is defined as the resistance created by a porous structure, independent of the flowing fluid. The applicability of the law is confined to incompressible, Newtonian fluids and laminar flows under isothermal conditions, which are assumed throughout this work, so that the viscosity depends on the shear rate only. As demonstrated in Section 2.3, the silicone oils in this study exhibit shear-thinning flow behavior at elevated shear rates. It is evident that the fluid's viscosity is altered in accordance with the magnitude of the shear rate. Consequently, the fundamental assumption of Darcy's law, namely constant viscosity, is no longer valid. It is evident that both the flow velocity and the viscosity are contingent on the pressure gradient. Consequently, a linear function is inadequate for describing the relationship between velocity and pressure loss for shear-thinning fluids. In order to obtain a linear equation for the flow rate as a function of pressure loss, it is necessary to define an effective viscosity, denoted here

Table 3

Overview of selected features, target variable and dataset structure.

Index i	Δp bar	R_m m^{-1}	L m	d_p μm	η_0 Pa·s	λ s	v $m \cdot s^{-1}$
1	$X_{1,1}$	$X_{1,2}$	$X_{1,3}$	$X_{1,4}$	$X_{1,5}$	$X_{1,6}$	y_1
2	$X_{2,1}$	$X_{2,2}$	$X_{2,3}$	$X_{2,4}$	$X_{2,5}$	$X_{2,6}$	y_2
...	...	...	...	...	...	...	...
i	$X_{i,1}$	$X_{i,2}$	$X_{i,3}$	$X_{i,4}$	$X_{i,5}$	$X_{i,6}$	y_i

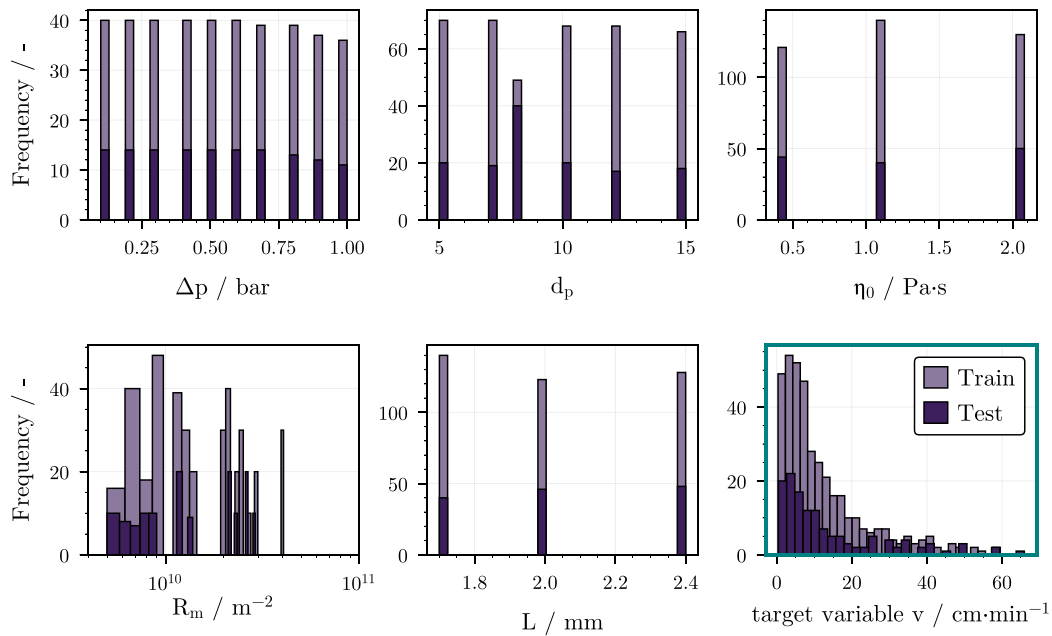


Fig. 3. Frequency of the target variable v and different features in the training and test dataset. Feature λ is distributed identically to feature η_0 and therefore not displayed.

Table 4

Mean sample skewness and excess kurtosis of the pooled out-of-fold log-space residuals for the three model types, given as mean $\pm$ standard deviation across the ten random seeds (0–9).

Model type	Mean sample skewness	Mean sample excess kurtosis
BBM- $\ln(y)$	-0.11 ± 0.55	0.58 ± 0.95
BBM- $y/\Delta p - \ln(y)$	-0.48 ± 0.43	0.13 ± 1.06
HBM	-0.06 ± 0.25	-0.76 ± 0.27

by η_{eff} . The modified form of Darcy's equation resulting from this assumption based on Eq. (6) serves as a white box model in this work. The effective viscosity is dependent on the porous medium, the pressure loss and the rheology of the fluid.

$$v = \frac{\Delta p}{R_m L \eta_{eff}} \quad (6)$$

There are various models that describe the effective viscosity for non-Newtonian fluids and porous media. Sadowski and Bird (1965) proposed a model that calculates the effective viscosity based on an approach derived from the Ellis model to describe the flow behavior. However, it should be noted that this approach requires an empirical correction factor that depends on the porous medium. A mathematically rigorous alternative is provided by homogenization theory. Bourgeat et al. (2001) derived an effective macroscopic law for the flow of Carreau fluids through thin periodic filters directly from the microscopic Stokes problem. While this approach avoids empirical corrections, it requires the numerical solution of nonlinear microscopic cell problems for each combination of pore geometry and fluid, and it has been formulated for single-layer filters with a simple periodic structure. For multilayer sintered composite-cloths, the representative unit cell comprises several stacked layers of different weave types, whose interaction has been shown to significantly influence the overall pressure drop (Bennett et al., 2024). An extension of the homogenization approach to such structures is therefore computationally demanding and, in contrast to the approach pursued here, does not rely on quantities that are readily available in industrial practice. An alternative approach was proposed by Eberhard

et al. (2019), which calculates the effective viscosity as the spatial mean value of the local viscosity within a representative capillary geometry. The pore space is described by a single cylindrical capillary with a characteristic radius. The semi-analytical solution of the Navier-Stokes equation provides local shear rates that are integrated over the cross-section, without the necessity for empirical correction factors. However, the transferability to real porous media is limited because the complex pore space geometry is idealized. To overcome this limitation, several modeling approaches are pursued and compared in this work: a purely data-driven black box model, a variant thereof with a feature-based target scaling, and a hybrid model combining the white box model with a data-driven correction. These approaches, described in the following sections, eliminate the need for empirical correction factors or substantial simplifications of the geometry.

2.4.3. Black box model

The first model developed in this study is a purely data-driven black box model. Instead of describing the flow velocity through the physically motivated relation in Eq. (6), the BBM learns the dependence of the flow velocity on the pressure loss, the geometry of the filter medium, and the rheological properties of the fluid directly from the experimental data. Therefore, the open-source framework Light Gradient Boosting Machine (LightGBM) in python was used. LightGBM is an efficient implementation of gradient boosting, based on decision tree learning algorithms. Gradient boosting method is an ensemble learning method, which combines the predictions from multiple models to generate a unified prediction (Géron, 2019). It works by sequentially adding predictors to an ensemble, with each new predictor correcting the residual errors of its predecessor. In LightGBM, a predictor is represented by a decision tree, and each tree is trained on the residuals of its predecessors. Consequently, the ensemble is gradually expanded. Choudhury et al. (2024) give a more detailed overview of the key concepts of LightGBM.

Since LightGBM serves as the data-driven regression algorithm for all three model types developed in this study, the training and hyperparameter optimization procedure described in the following applies equally to all of them. Hyperparameters were optimized using Bayesian optimization implemented in the Optuna framework. The default Tree-structured Parzen Estimator (TPE) sampler was used to sequentially explore the hyperparameter space. In each of the 50 optimization trials,

the candidate hyperparameter configuration was evaluated via stratified group 5-fold cross-validation on the training dataset, following the grouping and stratification scheme described in Section 2.4.1, with the mean squared error serving as the objective function. The same hyperparameter search space, summarized in Table 5, was used for all models. The resulting best configurations of all model variants are listed in Table B.9–16 of Appendix A. The corresponding convergence plots of the hyperparameter optimization for all model variants are provided in Section C of Appendix A.

The structure of the three model types is illustrated in Fig. 4. For the purely data-driven BBM, the input features comprise the pressure loss Δp , the geometric pore size d_p of the filter medium, and the rheological properties of the fluid given by η_0 and λ . The target variable is the apparent velocity v . The flow resistance of composite-cloths used as input feature is based on standardized air permeability measurements, as these represent the industrial standard for characterizing filter media (Purchas and Sutherland, 2002).

For training the mean squared error (MSE) was employed as the loss function, minimizing the average squared deviation between the predicted values $\hat{y}_i$ and the true values y_i . In this context, r denotes the total number of samples.

$$MSE = \frac{1}{r} \sum_{i=1}^r (y_i - \hat{y}_i)^2 \quad (7)$$

To evaluate the trained model's predictive performance, the mean absolute percentage error (MAPE) was utilized, as shown in Eq. (8). In order to ensure comparability of the results, the reported mean absolute percentage error (MAPE) values are based on the same test dataset.

$$MAPE = \frac{100}{r} \sum_{i=1}^r \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (8)$$

2.4.4. Black box model with feature-based target scaling

Building on the purely data-driven BBM, two further model variants were implemented. The second pipeline incorporates a feature-based target scaling. As illustrated in Fig. 4, the model structure remains that of a pure black box model. However, instead of being trained on the target variable directly, the model is trained on the flow velocity divided by the pressure drop. The rationale behind this scaling is that the flow velocity spans roughly three orders of magnitude in the dataset, and it exhibits a strong, nearly affine primary dependence on the pressure loss. Dividing the target by Δp removes this dominant linear dependence, so that the model only needs to capture the remaining, weaker nonlinear effects. Since the scaled target is subsequently log-transformed as described in Section 2.4.1, the model predictions are first back-transformed to the original scale, including the bias correction according to Eq. (8), and then multiplied by the respective pressure drop. This final step recovers the flow velocity v as the actual quantity of interest, ensuring that all model variants are evaluated on the same target variable. The training procedure, the cross-validation scheme, and the hyperparameter search space remain identical to the pipeline introduced in the previous section. This model variant is referred to as BBM- $y/\Delta p$ -ln(y) in the following.

2.4.5. Hybrid model

The last two models developed in this work combine the WBM based on the modified Darcy's law in Eq. (6) with a BBM based on the

LightGBM algorithm as described in Section 2.4.3. Such combinations are frequently referred to in literature as a hybrid or grey box model (HBM) (Bikmukhametov and Jäschke, 2020; Chen and Ierapetritou, 2020; Sharma and Liu, 2022; Zhai et al., 2024). Integrating the advantages inherent in both approaches has been demonstrated to result in a significant improvement in the modeling outcome (Conlin et al., 1997). BBMs have proven effective in capturing complex nonlinear relationships, even in the absence of explicit prior knowledge (Banerjee et al., 2021; Ní Mhurchú and Foley, 2006; Raman and Klima, 2019; Zhang et al., 2020), whereas WBMs offer distinct advantages in terms of physical consistency and interpretability. In addition, training a robust model often requires less data when using a combination of a BBM and a WBM compared to using a pure BBM (Psichogios and Ungar, 1992). In addition to the selection of adequate WBMs and BBMs, the configuration of the HBM should not be underestimated with respect to the modeling outcome (Chen and Ierapetritou, 2020; Zhai et al., 2024). In general, there are two types of configurations: a parallel and serial interconnection. They differ in the way the submodels are connected to each other. In a parallel structure, the two models are trained simultaneously. The BBM learns the residuals between the WBMs calculation and the experimental data. These residuals may be attributable to unreasonable assumptions or strong simplifications of the WBM. In this HBM structure, the BBM is responsible for estimating the error of the WBM and subsequently compensating for it (Bhutani et al., 2006; Keskitalo and Leiviskä, 2015; Menesklou et al., 2021; von Stosch et al., 2014). In the second structure of hybrid models, the connection is made serially. In this configuration, the two models are interconnected in such a way that the BBM predicts parts that are not known to the WBM. This is particularly advantageous when parts of the WBM are too complex, unavailable, or unsuitable for mapping the real process (Alhajree et al., 2011; Bazaei and Majd, 2003; Bollas et al., 2003; Chen and Ierapetritou, 2020; Oliveira, 2004).

In this work, both configurations were implemented and are compared in the results section. In the serial structure, as shown in Fig. 4, the change in effective viscosity in the WBM is not described mechanistically, but replaced by the BBM. First, the BBM predicts the inverse effective viscosity based on the pressure loss, the flow resistance of the composite-cloth, the thickness of the composite-cloth, the geometric pore size of the finest cloth layer, the zero-shear viscosity, and the time constant of the Carreau–Yasuda model. The WBM then calculates the flow velocity via Eq. (6) using this prediction as input. The black box submodel is thus embedded in the physical structure of Darcy's law, accounting for the unknown rheological behavior in the pore space. It should be noted that, since the BBM receives Δp as an input, this serial architecture does not enforce the linear $v - \Delta p$ relationship that Darcy's law prescribes for Newtonian fluids. This flexibility is intentional, because for shear-thinning fluids, the effective viscosity depends on the local shear rate, which itself varies with the applied pressure loss, so the nonlinear $v - \Delta p$ behavior must be captured by the BBM. The physical prior knowledge thus enters the model through the multiplicative Darcy structure and the cloth-specific parameters R_m and L .

In the parallel structure, as shown in Fig. 4, the WBM first calculates the flow velocity according to Eq. (5), using the zero-shear viscosity of the fluid. Subsequently, the BBM is trained on the residuals between the WBM prediction and the experimental data, using the pressure loss, the flow resistance of the composite-cloth, the thickness of the composite-cloth, the geometric pore size of the finest cloth layer, the zero-shear viscosity, and the time constant of the Carreau–Yasuda model as input features. The final prediction of the parallel HBM is obtained as the sum of the WBM output and the residual predicted by the BBM. The training procedure, cross-validation scheme, and hyperparameter search space of the black box submodels remain identical to the pipeline introduced in Section 2.4.3 for both hybrid configurations.

Table 5
Hyperparameter range used in the optimization during cross validation.

Hyperparameter	Range	Sampling
Number of estimators	50 - 1000	Uniform
Max. depth	3 - 12	Uniform
Max. number of leaves	8 - 256	Uniform
Learning rate	0.001 - 0.3	Log-uniform

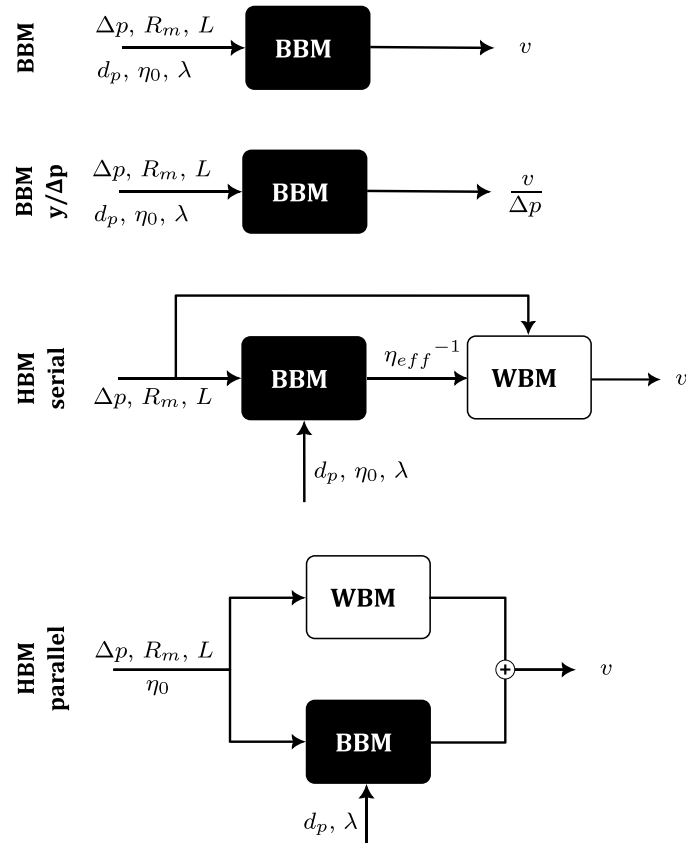


Fig. 4. Schematic representation of the four model structures: the pure black box model (BBM), the black box model with feature-based target scaling (BBM- $y/\Delta p$) and the hybrid models in serial (HBM-serial) and parallel (HBM-parallel) configuration, as well as relevant input parameters and target value. All model structures were also trained with a logarithmic transformed target variable.

3. Results and discussion

To investigate the influence of the flow behavior of the fluids used, the modified Darcy law given in Eq. (6) was applied. On this basis, the effective resistance R_{eff} was defined as follows and calculated for the individual experiments:

$$R_{eff} = L R_m \quad \eta_{eff} = \frac{\Delta p}{v} \quad (9)$$

Fig. 5 shows the effective resistance as a function of pressure loss for composite-cloth B with flow through of silicone oil O2. The data series

refer to cloth B with different geometric pore sizes of the finest layer in the composite, ranging from 5 to 15 μm . As expected, the composite-cloth with the smallest geometric pore size exhibits the highest resistance. It is more than twice as high as that of the cloth with a geometric pore size of 15 μm .

When examining the calculated effective resistances at increasing pressure differences, a downward trend can be observed. In particular, the composite-cloth with a geometric pore size of 5 μm shows a decrease in effective resistance of 15.2% for pressure differences up to 1 bar. This downward trend becomes less pronounced for larger geometric pore sizes. For a pore size of 15 μm , the decrease up to 1 bar is only 5.4%. This

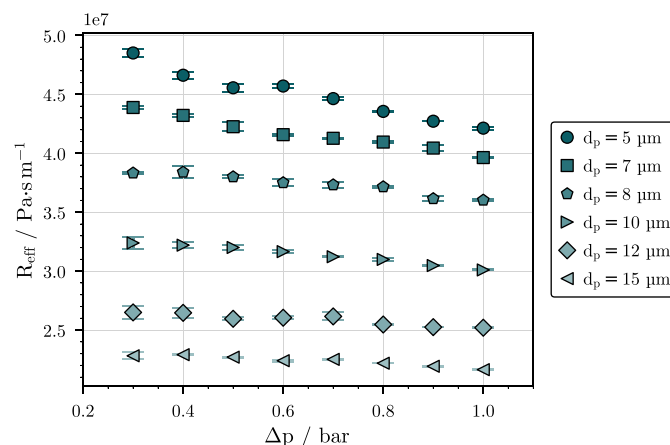


Fig. 5. Effective resistances R_{eff} calculated according to Eq. (9) for the composite-cloth B and the experiments with silicone oil O2.

observation can also be seen in composite-cloth A and C. These results indicate that the flow behavior cannot be adequately described by Darcy's law alone. The observed decrease in effective resistance can be attributed to changes in the effective viscosity of the fluid and its shear-thinning behavior, as the intrinsic filter medium resistance and the thickness of the composite-cloth remain constant. The change in effective resistance is clearly dependent on composite structure regarding the geometric pore size and the pressure loss. To map the relationships between changes in flow behavior, composite-cloth and pressure loss, this paper proposes data-driven and hybrid modeling approaches.

In addition to a purely data-driven BBM and a variant with feature-based target scaling, two hybrid models are employed to supplement Darcy's law and to capture the shear-thinning behavior of the fluid penetrating the composite-cloth. The structure of all models is described in detail in Section 2.4. The primary benefit of a hybrid model is its greater flexibility in comparison to purely knowledge-based models, while still adhering to the restrictions imposed by the WBM (Narayanan et al., 2023). It has been demonstrated that pure BBM tend to learn relationships from datasets, independent of whether these relationships are physically meaningful or spurious, which necessitates large datasets to ensure generalizability (Hawkins, 2004; Schubert et al., 1994). Moreover, unlike a fully knowledge-based model, a hybrid approach does not require detailed descriptions of the complex flow conditions in composite-cloths. Whether these conceptual advantages translate into superior predictive performance for the present application is examined in the following by comparing all model variants. In addition, the influence of the logarithmic transformation of the target variable, introduced in Section 2.4.1 is evaluated by training each model both with and without this transformation.

For this purpose, all models are evaluated on the test dataset consisting of previously unseen data, which was isolated from the total dataset as described in Section 2.4.1. Fig. 6 shows the resulting mean absolute percentage error (MAPE) for all model variants with and without log-transformed target. Since the entire pipeline was executed with ten different random seeds, the markers represent the mean MAPE across all seeds and the error bars its standard deviation. The MAPE of the purely physics-based WBM is indicated as a horizontal reference line. Although the WBM itself contains no random components, its evaluation is subject to the seed-dependent train-test split. For each seed, the MAPE is computed on the corresponding test set. The solid line therefore represents the mean WBM error across the ten test sets and the dashed lines its standard deviation, ensuring that all models, including the WBM, are compared on identical test data for each seed. Three main observations can be made. First, the logarithmic transformation, a common tool for unevenly distributed targets (Géron, 2019), enhances the performance of all model variants. For each architecture, the

log-transformed variant, referred to as $-\ln(y)$, yields a lower mean MAPE than its untransformed counterpart. A comparison of the log-transformed variants with and without the Baskerville bias correction shows that the improvement stems almost entirely from the transformation itself, which compresses the skewed target distribution. The correction merely compensates the systematic underestimation introduced by the exponential back-transformation and reduces the mean MAPE by only 2–7 percentage points. It is applied identically to all log-transformed variants and therefore does not affect the comparison between models. Second, all data-driven and hybrid models outperform the WBM baseline by a clear margin. Among them, the hybrid structures achieve the lowest errors, with the parallel HBM- $-\ln(y)$ performing best at a mean MAPE of approximately $5.59 \pm 1.85\%$. However, the error bars of the best-performing hybrid models partly overlap with those of the BBM- $-\ln(y)$, indicating that the advantage of the hybrid structures over the purely data-driven model is moderate relative to the seed-induced variability. Third, the feature-scaled BBM- $y/\Delta p$ - $-\ln(y)$ exhibits the smallest standard deviation across seeds of all model variants. Its predictions are thus the least sensitive to the random train-test split, making it the most stable configuration, albeit at the cost of a slightly higher mean error than the hybrid structures.

In the following, only the models trained with log-transformed target variables are discussed further. Among these, the BBM- $-\ln(y)$, the HBM-serial- $-\ln(y)$, and the HBM-parallel- $-\ln(y)$ achieved the lowest errors and are therefore compared in more detail. Although the error bars of these three models partly overlap in Fig. 6, such a comparison of aggregated errors does not exploit the paired structure of the results. Since all models are evaluated on identical test sets for each seed, their MAPE values can be compared seed-wise. Fig. 7 shows the resulting paired MAPE differences, and Table 6 summarizes the corresponding two-sided Wilcoxon signed-rank tests with Holm-corrected p-values. Both hybrid structures achieve a lower MAPE than the purely data-driven BBM- $-\ln(y)$ in nine out of ten seeds, a difference that is statistically significant under the paired Wilcoxon test. Given the limited number of ten seeds and the overlapping data splits out of one dataset, these p-values should be interpreted as supporting evidence for a consistent trend rather than as definitive proof. Furthermore, the seed-wise comparison reveals that the parallel configuration outperforms the serial one, with a median difference of 1.24 percentage points, likewise in nine out of ten seeds. Consequently, a consistent ranking emerges across nearly all data splits and the parallel hybrid structure is therefore the preferred configuration for the present application.

For a more detailed assessment beyond the aggregated error metrics, Fig. 8 shows the parity plots and corresponding residuals of the three best-performing models, evaluated on the seed-dependent test sets. All three models follow the ideal line closely, with the majority of

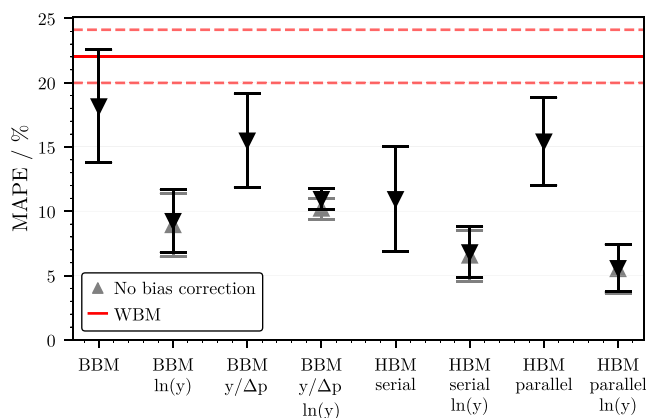


Fig. 6. The MAPE on the test set for all model variants, trained with and without logarithmic transformation of the target variable. Markers represent the mean across the ten random seeds.

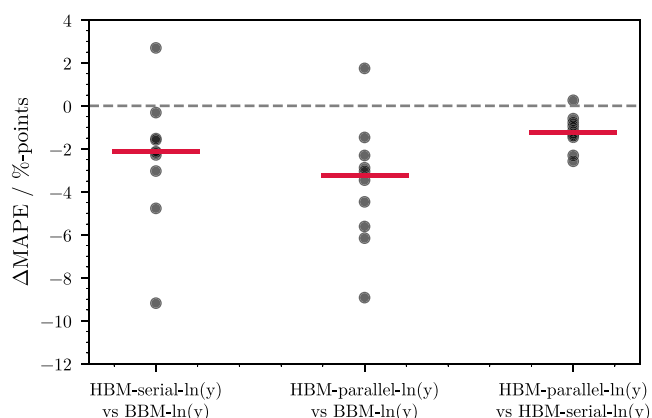


Fig. 7. Paired MAPE differences across the ten random seeds for the three model comparisons. Red lines indicate the median and negative values favor the first-named model.

Table 6

Paired comparisons of the test-set MAPE across the ten random seeds using two-sided Wilcoxon signed-rank tests with Holm-corrected p-values. Negative median differences indicate a lower error of the first-named model. The quantity m denotes the number of seeds out of ten in which the first-named model achieved the lower MAPE.

Comparison	Median Δ MAPE in %-points	m	Holm-corrected p
HBM-serial-ln(y) vs. BBM-ln(y)	-2.15	9	0.037
HBM-parallel-ln(y) vs. BBM-ln(y)	-3.25	9	0.012
HBM-parallel-ln(y) vs. HBM-serial-ln(y)	-1.24	9	0.012

predictions lying within the $\pm 15\%$ band. Notably, the purely data-driven BBM-ln(y) already captures the underlying correlations with a MAPE of $9.25 \pm 2.32\%$, demonstrating that the dataset is sufficiently informative and that the input variables listed in.

Table 3 are suitable for the prediction task. The residual plots reveal a common pattern: for all models, the residual scatter increases with the predicted velocity, reflecting the multiplicative error structure of the process. The models differ, however, in the magnitude of this scatter: the BBM-ln(y) exhibits the largest spread of the residuals around zero, followed by the HBM-serial-ln(y), while the HBM-parallel-ln(y) shows the narrowest residual distribution over the entire velocity range, in line with its lowest MAPE of $5.59 \pm 1.76\%$.

To further evaluate the parallel HBM and compare it with the pure WBM, the flow velocity predictions for three selected data series, listed in Table 7, are discussed in the following. The series, denoted a, b, and c, are complete groups of the test set of seed 0, assigned by the stratified group-based split described in Section 2.4.1.

The schematic in Fig. 9 illustrates the prediction process of the HBM-parallel-ln(y) and, in particular, the required input quantities. The prediction relies on three groups of information: first, the flow resistance of the composite-cloth, obtained from a standardized air permeability measurement, second, the geometric characteristics of the composite-cloth, namely the minimum pore size and the thickness, and third, the fluid properties, namely the zero-shear viscosity and the characteristic time constant of the Carreau-Yasuda model. Based on these inputs, the flow velocity can be predicted for any given pressure difference.

As illustrated in Fig. 10, the experimental measurement data is

presented alongside the HBM-parallel-ln(y) prediction and the calculation of the pure WBM according to Darcy for the data series described in Table 7. The parallel HBM-ln(y) predictions are predicted according to the scheme in Fig. 9. The WBM is calculated using Darcy's law from Eq. (5) with a flow resistance derived from experimental data corresponding to the test data points.

Table 7

Excerpt from the test dataset with samples aggregated according to the stratified group-based split at the beginning of the pipeline with a seed of 0. Data series corresponds to Fig. 10.

Data series	d_p	L	η_0
a	7	1.7	1.12
b	8	2.4	1.12
c	7	2.4	2.08

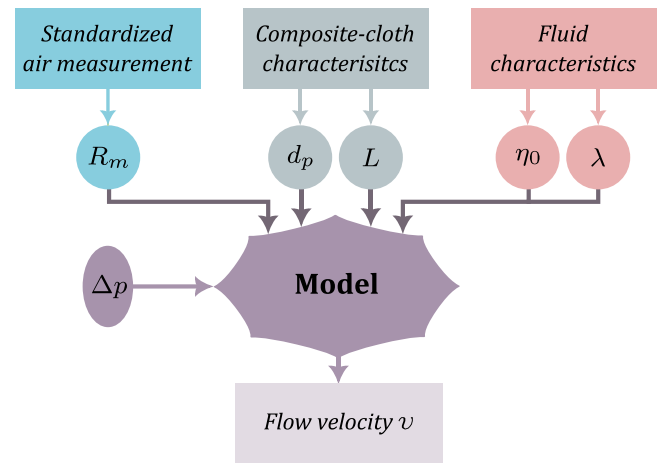


Fig. 9. Schematic sequence for predicting the flow velocity beginning with a standardized air measurement to determine the flow resistance of the composite-cloth. Based on the characteristic parameters of the composite-cloth and the fluid, the flow velocity can then be predicted for any given pressure loss.

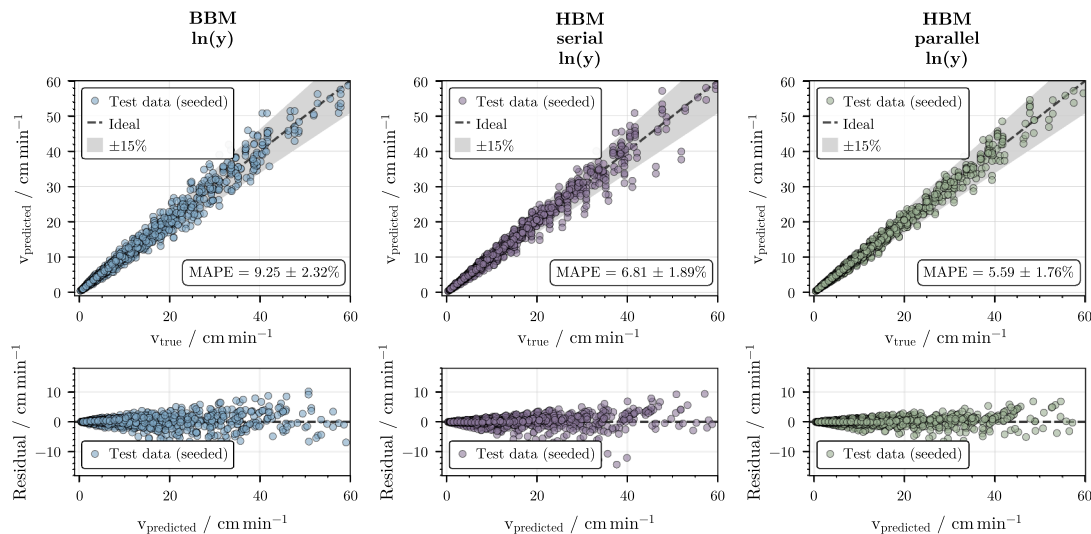


Fig. 8. Parity plots (top) and residuals versus predicted values (bottom) of the BBM-ln(y), HBM-serial-ln(y), and HBM-parallel-ln(y) on the test data. Each panel shows the pooled test predictions of all ten random seeds. The reported MAPE is given as mean $\pm$ standard deviation across the seeds. The shaded area indicates a $\pm 15\%$ deviation from the ideal line.

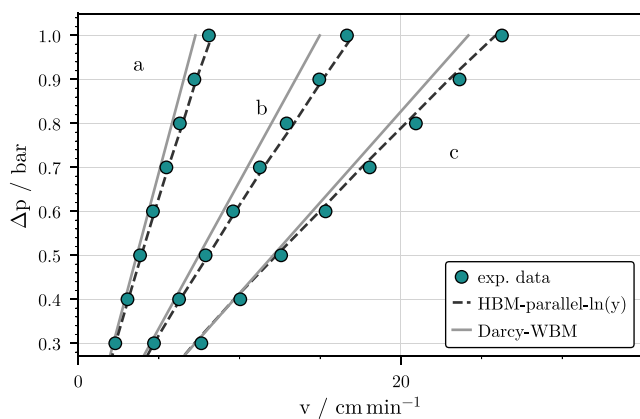


Fig. 10. Prediction of the velocity using the test dataset of seed 0 with more information shown in Table 7.

It is evident that the WBM, as described by Darcy, provides a satisfactory coverage of measurement data at low pressure differences and, consequently, at reduced flow velocities. However, the deviation of the WBM is observed to raise up with increasing velocity. As demonstrated in Fig. 10, at a pressure difference of 1 bar, the experimental data deviates by up to 15% and overestimates the pressure loss at a defined velocity. In contrast, the HBM-parallel-ln(y) has been demonstrated to successfully cover experimental data even at high velocities. It is evident that, for data series c, the HBM-parallel-ln(y) exhibits a tendency to slightly overestimate the experimental data. To evaluate the overall performance, the MAPE was computed on the seed-dependent test sets and averaged across the ten seeds. The HBM-parallel-ln(y) presented here enables the prediction of velocity with a MAPE of $5.59 \pm 1.85\%$. Conversely, the pure WBM, with its linear relationship results in a MAPE of $22.05 \pm 2.07\%$ and is therefore insufficient to account for the shear-thinning flow behavior.

4. Conclusions

The present paper proposes and systematically compares data-driven and hybrid modeling strategies for describing the flow velocity of non-Newtonian fluids through multilayer sintered metal wire composite-cloths. In the hybrid models, a WBM based on Darcy's law, which accurately describes the flow of Newtonian fluids through porous media, is combined with a BBM that captures the nonlinear contributions arising from the shear-thinning rheological behavior of the fluids. Both a serial and a parallel configuration were implemented and benchmarked against a purely data-driven BBM as well as the pure WBM, with all pipelines repeated across ten random seeds and compared using paired statistical tests. Both hybrid configurations outperformed the purely data-driven approach, with the parallel structure achieving the lowest prediction error of MAPE of $5.59 \pm 1.85\%$. These findings demonstrate that the incorporation of physical prior knowledge improves the prediction accuracy and robustness within the investigated parameter space. It should be emphasized that this constitutes interpolation within the examined range of cloth architectures, fluids, and operating conditions rather than generalization beyond it. A particular added value of this work is the application of hybrid modeling to multilayer sintered composite-cloths, a material class for which no such approach has been reported. In addition, the practical selection of input variables enables the prediction of the flow velocity based solely on standardized air permeability measurements of the composite-cloths together with the rheological parameters of the fluid, quantities that are readily available in industrial practice. Extending the model beyond the current scope requires several steps. True generalization to unseen cloth architectures or fluids should be assessed via leave-one-cloth-out and leave-one-fluid-

out evaluations, which demand an expanded dataset covering a broader range of composite-cloths and non-Newtonian fluid classes. Furthermore, incorporating temperature as an input variable would allow the isothermal restriction of the present study to be lifted. However, within the scope of the current dataset, the implemented approach already extracts sufficient information from the available input quantities.

Abbreviations.

Symbol	Description	Unit
d_p	Geometric pore size	μm
i	Index of data points	-
f	Feature	-
j	Index of stratified groups	-
L	Thickness	m
n	Exponent	-
m	Number of seeds	-
Δp	Pressure Loss	bar
r	Total number of samples	-
R_m	Media resistance	m^2
R_{eff}	Effective resistance	m^2
v	Velocity	$\text{m}\cdot\text{s}^{-1}$
$X_{i,f}$	Data point	-
$\hat{y}_i$	Predicted values	$\text{m}\cdot\text{s}^{-1}$
y_i	Target values	$\text{m}\cdot\text{s}^{-1}$
z_i	Transformed target values	$\text{m}\cdot\text{s}^{-1}$
$\hat{z}_i$	Predicted transformed values	$\text{m}\cdot\text{s}^{-1}$
α	Transition Parameter	-
$\dot{\gamma}$	Shear rate	s^{-1}
η	Viscosity	Pa·s
η_{eff}	Effective viscosity	Pa·s
η_{∞}	Limiting shear viscosity	Pa·s
η_0	Zero-shear viscosity	Pa·s
λ	Time constant	s
ρ	Density	$\text{kg}\cdot\text{m}^{-3}$
BBM	Black box model	
HBM	Hybrid model	
LightGBM	Light Gradient Boosting Machine	
MAPE	Mean absolute percentage error	-
MSE	Mean squared error	$\text{m}^2\cdot\text{s}^{-2}$
WBM	White box model	

Declaration of generative AI in scientific writing

During the preparation of this work the authors used the ChatGPT-5 exclusively for grammar improvement, stylistic refinement, and consistency checking. All scientific content, analyses, and interpretations were created and verified by the authors. The authors reviewed and approved all edits to ensure accuracy and integrity of scientific meaning.

CRediT authorship contribution statement

Melanie Fuhrmann: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Rehm:** Writing – review & editing, Data curation. **Martin Müller:** Writing – review & editing. **Hermann Nirschl:** Writing – review & editing, Funding acquisition. **Marco Gleiß:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.dche.2026.100341](https://doi.org/10.1016/j.dche.2026.100341).

Data availability

All data used in this study is available at KITopen / Radar (Fuhrmann and Rehm, 2026).

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