

Preliminary framework for physics-informed AI application to heat transfer in minichannel heat exchangers

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Abstract. This paper outlines a preliminary concept for applying physics-informed machine learning to analyse and correlate flow boiling heat transfer in minichannel heat exchangers. The framework is conceptual and is intended to guide future integration of experimental data with data-driven modelling. The Random Forest method is proposed as a candidate algorithm due to its interpretability and ability to capture nonlinear interactions among key dimensionless parameters. The study presents the planned workflow, feature engineering principles, and validation strategy to ensure physical consistency. The expected result is a preliminary methodological framework linking experimental and theoretical perspectives on heat transfer. Future work will extend this concept through comprehensive data acquisition, benchmarking, and analytical correlation development.

1 Introduction

Minichannel heat exchangers have become the keystone of modern thermal management systems used in microelectronics cooling, heat pumps, energy recovery modules, and high-performance power electronics. Their small hydraulic diameters, extended heat transfer surfaces, and high surface-to-volume ratios enable efficient phase-change heat removal under limited space and low refrigerant charge conditions. However, miniaturisation of flow passages leads to complex interactions between capillary, viscous, and inertial forces, which cause nonuniform liquid-vapour distributions and local temperature fluctuations. These effects make it difficult to predict heat transfer and pressure drop using conventional design correlations.

Compact heat exchangers are increasingly being used in sectors such as data centres, e-mobility, and hydrogen technologies, where thermal control at high heat fluxes must coexist with environmental sustainability. The shift toward low-GWP refrigerants and dielectric fluids introduces new thermophysical characteristics that alter the boiling behaviour and demand new design methods based on data-driven and physics-consistent modelling.

Traditional empirical or semi-empirical models, developed for macroscale tubes, often fail to account for the microscale mechanisms dominating in minichannels - such as confinement effects, surface roughness sensitivity, or the dominance of local bubble dynamics over bulk convection. As a result, heat transfer coefficients derived from existing correlations can differ from measured data by more than $\pm 50\%$ when applied

outside their calibration range. The scarcity of reliable experimental datasets, coupled with the diversity of channel geometries and working fluids, further limits generalisation. Accurate prediction of heat transfer in these compact geometries is essential for designing next-generation thermal systems that employ low-GWP refrigerants and environmentally safe working fluids. Therefore, there is a strong need to develop generalised and physically consistent correlations capable of extrapolating across fluids, surface treatments, and flow regimes.

The present paper outlines a preliminary physics-informed machine-learning (ML) framework for the analysis and correlation of flow boiling heat transfer data in minichannel heat exchangers. The framework is methodological and is intended to support follow-up studies focused on developing generalised, physically consistent heat-transfer correlations. Only a few studies have been reported in the literature on this topic [1, 2]. In follow-up work, using high-resolution, time-synchronised experimental data, ML models will be trained to identify nonlinear relationships and to generate physically constrained, dimensionless correlations for predicting the Nusselt number (Nu) or directly estimating the heat transfer coefficient (HTC); the corresponding trained-model results will be reported in future publications. The feature set includes dimensionless numbers such as Reynolds (Re), Prandtl (Pr), Bond (Bo), and Jakob (Ja), as well as parameters that describe geometry, orientation, and surface roughness. The present study draws on previous experience and sources from the literature [3–7].

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In parallel, theoretical correlations are developed to separate convective and nucleate boiling contributions to the overall HTC. These expressions are formulated as functions of key factors such as fluid type, minichannel geometry, and orientation, and also as applications of enhanced heated surfaces. The hybrid modelling framework, which combines experimental diagnostics, CFD simulations, and ML methods, aims to overcome the generalisation and interpretability limitations of well-known empirical models. Ultimately, future work will focus on providing predictive tools that are accurate, generalisable, and physically interpretable, supporting the design of compact thermal systems with enhanced performance.

2 Methodology: AI-based data analysis and correlation development

2.1 Physics-informed AI framework

Structured datasets combining minichannel heat exchanger geometry, working fluid properties, and thermal and flow parameters will be compiled from synchronised experimental measurements. The existing experimental database already provides a substantial foundation of relevant data. Selected AI techniques, primarily tree-based ensemble models and neural networks, will be employed to extract and generalise dimensionless correlations describing convective and flow boiling heat transfer.

The tree-based Random Forest (RF) is selected for machine learning analysis due to its robustness, interpretability, and ability to capture nonlinear feature interactions without extensive data preprocessing. This algorithm repeatedly partitions the feature space into many regions of similar thermohydraulic behaviour, automatically learning thresholds and interactions between dimensionless numbers (Re , Pr , Bo , and Ja) and geometric or surface descriptors. Its capacity to handle sparse and noisy data sets makes it particularly suitable for heat transfer research, where measurement uncertainty and non-uniform operating conditions are common. In contrast to purely black-box deep neural networks, tree-based models enable physical interpretability through feature importance ranking and partial dependence analysis, helping to reveal dominant mechanisms responsible for boiling enhancement or suppression. This approach will be applied in thermal and fluid studies to demonstrate that ensemble decision tree models can reproduce and, in many cases, outperform traditional empirical correlations while preserving interpretability.

In the proposed framework, the input features include Re , Pr , Bo , and Ja , as well as surface and geometric parameters. The output variables are the local Nusselt number and the heat transfer coefficients. Model optimisation involves cross-validation, hyperparameter tuning, feature importance ranking, and the introduction of physics-informed constraints to preserve monotonicity, dimensional consistency, and asymptotic behaviour in limiting flow regimes.

The final outcome will be a predictive, generalised correlation that unifies experimental and theoretical perspectives on heat transfer in minichannel flows of compact heat exchangers. Such correlations are expected to help designers accurately estimate heat transfer performance across a wide range of fluids and operating conditions while maintaining interpretability that supports physical insight.

In the current framework, several machine learning algorithms are considered to evaluate their predictive capability and interpretability for boiling heat transfer data. In addition to tree-based ensembles, support vector regression (SVR), Gaussian process regression (GPR), and feedforward neural networks (FNNs) are analysed to benchmark the performance of different model families.

SVR is suitable for small datasets with limited noise and allows analytical control of the bias variance trade-off. GPR provides not only point predictions, but also confidence intervals that are useful for uncertainty quantification in experimental measurements. Neural networks, while more flexible, require larger datasets and careful regularisation to avoid overfitting.

Comparative training across these model types highlights how physical features such as Reynolds, Bond, or Jakob numbers map onto output variables such as the local Nusselt number. Ensemble-averaged predictions are also explored, combining the strengths of multiple algorithms to improve robustness and stability under extrapolation. Model performance is evaluated using mean absolute percentage error (MAPE), R^2 metrics, and physical consistency checks to ensure monotonic behaviour with respect to the governing parameters. This multi-algorithmic strategy provides a deeper understanding of how different learning paradigms capture the nonlinear relationships in two-phase heat transfer and supports the selection of the most physically interpretable model for future correlation development.

Model validation will include cross-comparison with classical correlations and CFD simulations under controlled conditions. The goal is not to replace existing analytical formulations but to extend them toward broader parameter spaces while maintaining physical interpretability and dimensional homogeneity.

The long-term objective is to establish a bidirectional coupling between CFD solvers and AI modules. CFD-generated data will complement experimental measurements, enriching the training space for under-represented flow regimes, while trained AI models can accelerate CFD convergence by providing surrogate correlations for local HTC estimation.

2.2 Tree-based modelling framework for heat transfer correlations

The development of data-driven correlations for the Nusselt number will be carried out using a tree-based machine learning framework trained on synchronised experimental datasets. Each record includes local and global thermal and hydraulic quantities such as mass flux, heat flux, pressure, wall and bulk temperatures, and

flow visualisation parameters. The experimental data were preprocessed to calculate the local heat transfer coefficients and the corresponding Nusselt numbers. Dimensionless groups including Reynolds, Prandtl, Bond, and Jakob numbers will be derived together with basic geometric and surface descriptors related to channel orientation, aspect ratio, and wettability. Outliers will be removed and the consistency of the data will be checked by comparing the electrical power input with the increase in enthalpy of the working fluid.

The preliminary modelling approach considers gradient-boosted regression trees (GBRT) and related ensemble methods such as XGBoost and Random Forest. These algorithms are chosen for their predictive accuracy, interpretability, and ability to capture nonlinear interactions without extensive data normalisation. Simple physical constraints will be applied during model training to preserve relationships between the Nusselt number and its main predictors. A limited cross-validation procedure will be used to verify the generalisation capability.

Basic feature engineering and sensitivity analyses will be performed to identify key variables that influence heat transfer behaviour. Early model evaluation will focus on ensuring physically consistent trends, for example, increasing the Nusselt number with higher Reynolds or Prandtl numbers and saturation behaviour with respect to Bond or Jakob numbers. The results will provide a foundation for further refinement and expansion of the AI-based framework toward predictive, generalised heat transfer correlations.

2.3 Preliminary distillation and validation strategy

Although tree-based Random Forest methods offer high predictive accuracy, their internal structure does not directly yield compact analytical expressions. Therefore, it is planned to distill the trained GBRT model into a simplified analytical correlation suitable for engineering applications. The tree structure will be examined to identify characteristic subdomains in the feature space corresponding to different flow regimes and boiling intensities. Within each subdomain, symbolic regression (SR) will be applied to approximate the GBRT predicted Nusselt number using a limited set of mathematical operators, while penalising excessive algebraic complexity. This approach is expected to produce analytical forms with exponents consistent with dimensional analysis and physically meaningful monotonicity.

The preliminary family of correlations can be expressed in a general form as follows.

$$Nu = C_0 Re^{a_1} Pr^{a_2} [1 + C_1 Ja^{a_3}] [1 + C_2 Bo^{a_4}] [1 + C_3 We^{a_5}]^{\sigma(\varphi)} \Phi(\Pi_g) \quad (1)$$

where

$$\Phi(\Pi_g) = (1 + C_4(\varepsilon^+)^{a_6})(1 + C_5(D_h/L)^{a_7})(1 + C_6 \cos \theta) \quad (2)$$

represents the effect of the channel orientation. The coefficients C_i and exponents a_i will be determined by

regression fitting of the model output and validated using an independent subset of the data.

The interpretability of the proposed framework will be further examined using SHAP analysis to quantify the relative influence of each feature on the Nusselt number prediction. The preliminary ranking of importance, typically led by Reynolds, Jakob, and Bond numbers, is expected to remain consistent with classical boiling mechanisms. Physical consistency will be verified by analysing partial dependence curves and error maps to confirm that most data points fall within an acceptable deviation from the experimental values (for example, $\pm 20\%$). Validation on additional fluids and geometries not used in training will assess whether the distilled correlation maintains predictive accuracy and generalisability beyond the calibration domain.

For completeness, several alternative learning algorithms, including Support Vector Regression (SVR), Gaussian Process Regression (GPR), and feed forward neural networks (FNN), will also be evaluated as benchmarks. Although these approaches may achieve comparable accuracy for selected subsets of the data, tree-based ensembles are expected to offer superior robustness to noise and clearer physical interpretability of learnt dependencies. Ensemble averaging between selected models may further reduce variance and improve stability under extrapolation. The comparative study will help determine whether the proposed methodology provides a balanced compromise between predictive performance, interpretability, and adherence to physical principles, forming a solid basis for future development of data-driven heat transfer correlations.

The block diagram of the Random Forest-based correlation development workflow is illustrated in Fig. 1.

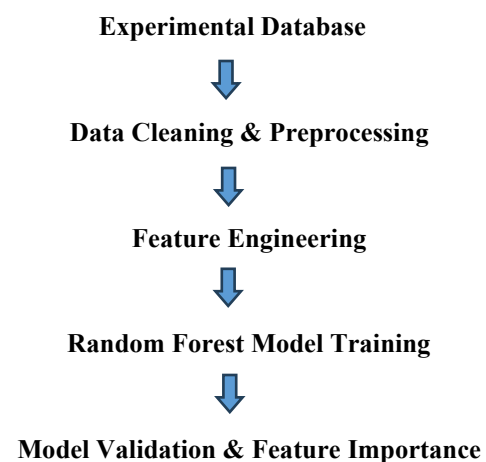


Fig. 1. Block diagram of the Random Forest-based correlation development workflow.

3 Experimental setup and techniques

3.1 Test sections

Modular and interchangeable test sections with rectangular and annular geometries were fabricated. They are described in many works of Piasecka's research group, as [8-12]. Rectangular channels are

machined into aluminium plates with integrated heating and insulation layers. These modules allow flexible reconfiguration of channel geometry and orientation for comparative studies. The annular configuration consists of a transparent inner tube and a metallic outer sleeve, providing optical access for flow observation. It should also be emphasised that some experiments were carried out using minichannels with a heated surface that was enhanced. Surface roughness modification methods can significantly improve boiling performance, as reported among others, in [13].

3.2 Working fluids and operating conditions

The research involves or is planned to involve a wide range of working fluids, including fluorinated dielectric liquids (HFE-649, HFE-7000, HFE-7100, HFE-7200, HFE-7300, FC-72, FC-770, Galden HT-55, HT-70, HT-80), distilled water, and other low-GWP working fluids.

Representative operating parameters are as follows:

- mass flux $50\div 800\text{ kg m}^{-2}\text{ s}^{-1}$,
- heat flux $10\div 200\text{ kW m}^{-2}$,
- inlet liquid subcooling $5\div 50\text{ K}$,
- absolute pressure $1\div 2.5\text{ bar}$.

3.3 Instrumentation

The experimental stand is located in the Laboratory of Boiling Heat Transfer at the Faculty of Mechatronics and Mechanical Engineering, Kielce University of Technology. Infrared thermography (FLIR thermal camera) is used for non-invasive temperature field mapping. Thermocouples of type T and type K monitor local wall and fluid temperatures, while a high-speed camera visualises flow regimes and interfacial behaviour. Pressure meters measure the inlet and outlet pressures of the test section, and Coriolis mass flow meters ensure accurate flow rate control. Programmable power supplies provide controlled heating input. Data acquisition and synchronisation are managed through NI DAQ modules and a LabVIEW interface.

The setup consists of parallel minichannels with rectangular cross-sections, having depths from 1 to 1.7 mm and lengths from 43 to 180 mm, mounted in variable orientations. The heating element is a thin Haynes-230 or Hastelloy X alloy plate that is resistively heated to supply heat to the working fluid. On the outer surface of the heater, the temperature distribution is recorded by the infrared camera, whereas flow structures are visualised through a transparent glass wall opposite the heated plate. Thermocouples and pressure sensors are installed at both ends of the minichannel. For annular configurations, the heater incorporates surface-mounted thermocouples along the flow path, and a glass tube forms the outer wall for flow visualisation. Interchangeable flanges allow precise control of the annular gap.

During the experiments, the measured quantities include mass flow rate, atmospheric pressure, inlet and outlet overpressures, working fluid inlet and outlet temperatures, heating wall surface temperatures and electrical parameters required for heat flux

determination. Infrared thermography is commonly used to obtain detailed temperature-field distributions, while high-speed imaging confirms the onset of nucleate boiling and facilitates the analysis of flow structures and regime transitions.

4 Results and outlook

The conducted experiments confirmed stable thermal and flow conditions, as well as high repeatability of temperature field acquisition and flow visualisation. The data obtained demonstrate that the measurement system ensures reliable synchronisation and sufficient accuracy for subsequent data-driven analysis.

The experimental results reveal physically consistent trends of the local heat transfer coefficient and Nusselt number with respect to dimensionless parameters such as Reynolds, Prandtl, Bond, and Jakob numbers. The observed behaviour reflects the expected transition from the thermal entrance region to the fully developed flow regime and confirms the strong influence of the fluid properties, channel geometry, and orientation on heat transfer performance.

The acquired database will serve as the basis for further analysis using physics-informed machine learning techniques. Future work will focus on developing and validating predictive correlations derived from these data, with benchmarking against classical and CFD-based models. Special attention will be paid to the effects of enhanced heating surfaces, variable orientations, and different working fluids.

Overall, the present study establishes a reliable experimental basis for subsequent implementation of AI-assisted modelling, aimed at formulating generalised, physically consistent correlations for flow boiling in compact minichannel heat exchangers.

5 Validation and discussion

The experiments carried out confirmed stable operating conditions and consistent measurement accuracy across repeated test runs. The datasets obtained provide a reliable basis for evaluating heat transfer correlations under varying flow regimes, orientations, and working fluids.

The preliminary comparison of the measured results with selected classical correlations reported in the literature [14–29] shows satisfactory agreement within typical uncertainty limits for minichannel flow boiling. Differences observed at higher heat fluxes and for enhanced surfaces indicate areas where existing empirical models fail to capture microscale effects, such as capillary dominance and bubble confinement.

The collected data will be used in the next stage of research to train and validate physics-informed machine learning models. These algorithms are expected to extend the applicability of existing correlations to broader parameter ranges while preserving physical interpretability.

The validation procedure will include a quantitative comparison with traditional and CFD-based models,

sensitivity analysis of key dimensionless parameters, and uncertainty assessment.

Therefore, this phase of work establishes the experimental and methodological foundation for the subsequent development of a unified predictive framework that combines measured data, theoretical analysis, and data-driven modelling.

6 Conclusions

Comprehensive experimental investigations of flow boiling carried out using minichannel test sections, including newly designed modules, provide a reliable and repeatable database of thermal and hydraulic parameters. The obtained results confirm physically consistent relationships between the Nusselt number and key dimensionless parameters such as Reynolds, Prandtl, Bond, and Jakob numbers, as well as a strong influence of channel geometry, orientation, and surface characteristics on overall heat transfer performance.

The study outlines a preliminary framework for the application of physics-informed machine learning to analyse the experimental data and develop predictive correlations. The proposed methodology aims to combine physically grounded feature engineering with interpretable AI algorithms to extend existing heat transfer models and improve predictive accuracy within broader operating ranges.

The experimental database will serve as the foundation for this next stage of research, which will involve model training, benchmarking against CFD simulations and empirical correlations, and the derivation of simplified analytical expressions suitable for engineering use. The integrated application of experimental, numerical, and AI-based approaches is expected to enable the development of an accurate, interpretable, and generalisable predictive framework for flow boiling in compact minichannel heat exchangers.

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