



Accelerating Steel Casting CFD with Machine Learning

Urychlení CFD simulací odlévání oceli pomocí strojového učení

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Abstract

Computational Fluid Dynamics (CFD) is a critical tool for understanding flow behaviour in continuous steel casting, but high-fidelity simulations remain computationally intensive and time-consuming. This work presents a machine learning-based framework to accelerate CFD simulations by integrating reduced order modelling (ROM) with data-driven surrogate models. Using high-resolution CFD data, we show a workflow that trains machine learning models to approximate transient flow fields with high accuracy at a fraction of the computational cost. The resulting hybrid models aim to enable near real-time predictions of key process variables while preserving physical fidelity. This approach offers significant potential for in-line process optimization, faster design iterations, and intelligent control in modern steelmaking operations.

Keywords: CFD simulations, reduced order modelling, machine learning, continuous casting

Abstrakt

Výpočetní dynamika tekutin (CFD) je klíčovým nástrojem pro pochopení chování proudění při kontinuálním odlévání oceli, avšak vysoce přesné simulace zůstávají výpočetně i časově náročné. Tato práce představuje rámec založený na strojovém učení, který urychluje CFD simulace integrací modelování sníženého řádu (ROM) s datově řízenými náhradními modely. S využitím CFD dat s vysokým rozlišením je ukázán pracovní postup, jenž umožňuje trénování modelů strojového učení k aproximaci přechodových proudových polí s vysokou přesností při zlomek výpočetních nákladů. Výsledné hybridní modely umožňují téměř reálné predikce klíčových procesních veličin při zachování fyzikální věrnosti. Tento přístup nabízí významný potenciál pro optimalizaci procesů v reálném čase, rychlejší iterační návrhy a inteligentní řízení v moderních ocelářských provozech.

Klíčová slova: CFD simulace, modelování se sníženým řádem, strojové učení, plynulé lití

1. Introduction

Continuous casting processes in steel manufacturing involve complex unsteady flows of molten metal within molds, influenced by nozzle design, casting speed, applied magnetic fields, and mold geometry. CFD is indispensable for optimizing these processes but remains impractical for real-time applications due to high computational costs.

To meet industrial demands for faster design iteration and intelligent control, ROMs aim to compress high-dimensional CFD data into compact representations without compromising critical flow features. In steel plants, such models could be deployed for:

- Real-time control of mold filling and solidification,
- Predictive maintenance based on flow patterns,
- Fast prototyping of casting parameters and designs.



Recent developments in machine learning (ML) have significantly enhanced the capabilities of ROM for fluid dynamics, particularly in steel casting applications. These advancements aim to improve generalizability, computational efficiency, and the ability to capture complex flow behaviors. Key approaches include:

- **Dynamic Mode Decomposition (DMD):** A data-driven technique that decomposes transient flow fields into coherent structures governed by linear dynamics. DMD is particularly effective for analyzing laminar flows or systems where linear approximations are valid [1]. For parametric DMD, see e.g. [2].
- **Convolutional Residual Networks (ConvResNet):** By leveraging convolutional layers and residual connections, ConvResNets can capture spatial hierarchies and temporal dependencies in fluid flow data, making them suitable for modelling intricate flow patterns [3].
- **Neural Ordinary Differential Equations (Neural ODEs):** These models represent time-continuous latent dynamics through differential equations embedded within neural networks, allowing for flexible modelling of temporal evolution in dynamical systems [4].
- **Fourier Neural Operators (FNOs):** FNOs learn mappings between input functions and solutions to partial differential equations (PDEs) across varying parameter spaces, enabling efficient and accurate predictions of complex, nonlinear flow behaviors [5].
- **PDE-Preserving Neural Networks (PPNN):** PPNNs integrate discretized PDE operators directly into the neural network architecture, resulting that the learned models tend to fulfill the underlying physical laws better, thereby enhancing accuracy and generalizability [3].
- **NeuralDEM:** An end-to-end deep learning approach designed to replace traditional Discrete Element Method (DEM) simulations. NeuralDEM models particulate flows by treating the Lagrangian discretization as a continuous field and incorporating macroscopic behavior, enabling real-time simulations of industrial-scale particulate systems [6].

These ML-based ROM techniques offer promising avenues for accelerating CFD simulations in steel casting, with each method providing unique advantages depending on the specific flow characteristics and modelling requirements. Moreover, in [3] you can find a comparison of several different methods.

In this paper, only results of DMD and ConvResNet are discussed since some of the methods mentioned are more involved to implement/use.

2. Methodology

Integrating CFD- simulations with ML provides a powerful approach for predicting complex physical behaviors without the need for repeated high-cost simulations. The workflow begins with CAD model creation and proceeds through mesh generation and CFD simulations, followed by data preprocessing and ML model training. This enables faster design iterations and optimization. The **Fig. 1** illustrates the complete pipeline from CAD modelling to ML model development using CFD-generated data.

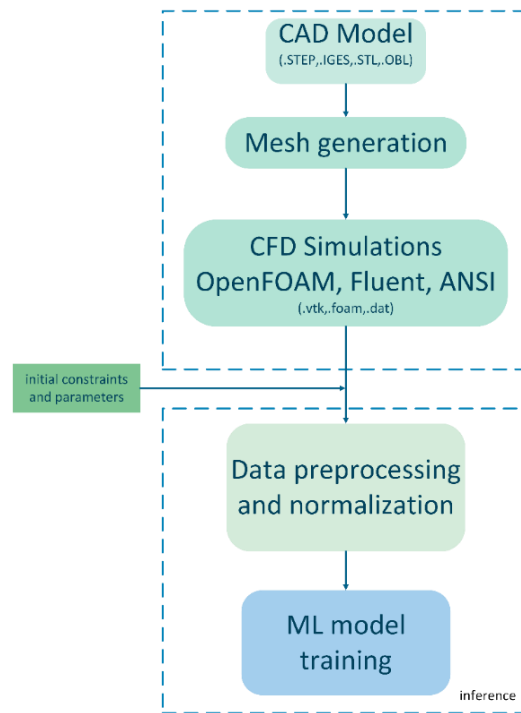


Fig. 1 End-to-end workflow for ML model development using CFD simulation data

Obr. 1 Komplexní pracovní postup pro vývoj modelů strojového učení s využitím dat ze simulací CFD

2.1 Governing Equations for Mold Flow

The Navier-Stokes equations are highly nonlinear and lack analytical solutions for most practical flows, so CFD employs the finite volume method to solve them numerically with conservation laws applied over discrete control volumes. In this study, Navier-Stokes equations are formulated under the assumptions of an incompressible, single-phase fluid that remains at a constant temperature throughout the flow. The continuity equation (1):

$$\nabla \cdot \mathbf{v} = 0 \quad (1)$$

represents the conservation of mass, stating that the divergence of the velocity field \mathbf{v} is zero for incompressible flows. The momentum equation (2) is given as:

$$\partial \mathbf{v} / \partial t + (\mathbf{v} \cdot \nabla) \mathbf{v} = -1/\rho \nabla p + \nu_{eff} \nabla^2 \mathbf{v} + \mathbf{f} \quad (2)$$

where ρ is the liquid steel density, p is the pressure, $\nu_{eff} = \nu + \nu_t$ is the effective viscosity, with ν and ν_t being the molecular and turbulent viscosity and \mathbf{f} represents the body forces.

In the case of mold flow, due to the high momentum of jets exiting the submerged entry nozzle (SEN), the flow of liquid steel is strongly turbulent. Turbulent flows involve a wide range of interacting scales in time and space. Here, this behavior is captured using the Reynolds-averaged Navier-Stokes equations (RANS). For turbulence closure, the two-equation eddy-viscosity approach, Shear Stress Transport (SST) $k - \omega$ model was employed.

2.2 Data Preparation

High-fidelity 3D simulations were conducted under various casting speeds, submergence depths and magnetic fields. 2D slices (e.g., mid-plane horizontal cross-sections) were extracted for training to reduce complexity while preserving dominant dynamics. One snapshot (see **Fig. 2**) every 0.1 s is taken over a total time of 60 s, which leads to a total of 601 snapshots per parameter set. In each 2D slice, the three velocity components are stored anyway and used for training the models.

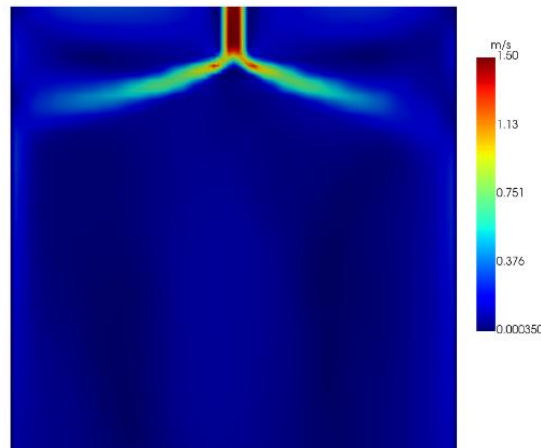


Fig. 2 Single snapshot of simulation. Shown is the absolute velocity combined from the three velocity components. The red part indicates where the entry nozzle is

Obr. 2 Samostatný snímek ze simulace. Zobrazena je absolutní rychlost, která je součtem tří složek rychlosti. Červená část označuje polohu vstupní trysky

2.3 Dynamic Mode Decomposition (DMD)

DMD approximates flow evolution using a linear operator A (3):

$$x_{k+1} \approx Ax_k \quad (3)$$

where snapshots x_k are flattened flow fields.

DMD excels at identifying laminar structures and oscillatory behavior, providing interpretable, low-rank models. For each simulation, one DMD model is trained and for new parameters, those models are interpolated, see e.g. [2] for more details.

2.4 Convolutional Residual Networks (ConvResNet)

ConvResNets integrate convolutional layers with residual (skip) connections, enabling the training of deeper networks by mitigating issues like vanishing gradients. In fluid dynamics, they effectively capture spatial hierarchies and temporal dependencies, making them suitable for modelling complex, nonlinear flow behaviors. By learning residual mappings, ConvResNets enhance generalization and stability in reduced-order modelling of unsteady flows.

3. Application and Results

3.1 Experimental Setup

- Training set: 12 high-resolution 3D mold flow simulations.
- Parameters: Inlet speed, nozzle submergence depth, applied magnetic field strength.
- Models: DMD (linear), ConvResNet.
- Model input: parameters (and initial snapshot for ConvResNet).
- Model output: Multi-step flow predictions.

3.2 Use of 2D Slices: Benefits and Limitations

Advantages:

- Lower memory and faster training.
- Good approximation for centerline symmetry flows.

Disadvantages:

- - May miss 3D effects (e.g., swirl, asymmetry).
- - Reduces physical completeness.

3.3 Results

DMD captured dominant laminar features well but deteriorated in turbulent regimes due to linearity limitations. However, in the tests conducted using parametric DMD, speed up factors of up to 50 were observed compared to traditional simulations.

Fig. 3 shows an example, where the interpolation seems to capture the dynamics in the mold quiet well. However, if we examine **Fig. 4**, we see that sometimes non-physical behavior can occur, depicted in this case as one jet splitting into two jets (right side of the right picture).

ConvResNet achieved lower relative errors in transient and nonlinear flow settings. It generalized across untrained parameters at least for the first few snapshots. The speedup is considerable with a factor of 1000. But after some time, error accumulation becomes a big issue with ConvResNet. This is a common problem with so called autoregressive neural networks.

In fact, ResNets can be interpreted as the explicit Euler method for an ordinary differential equation [4]. **Fig. 5** shows a result after short time, where it still produced seemingly good results, however, **Fig. 6** shows the result after 10 s and there already, a huge error accumulation took place and the result is not reliable at all.

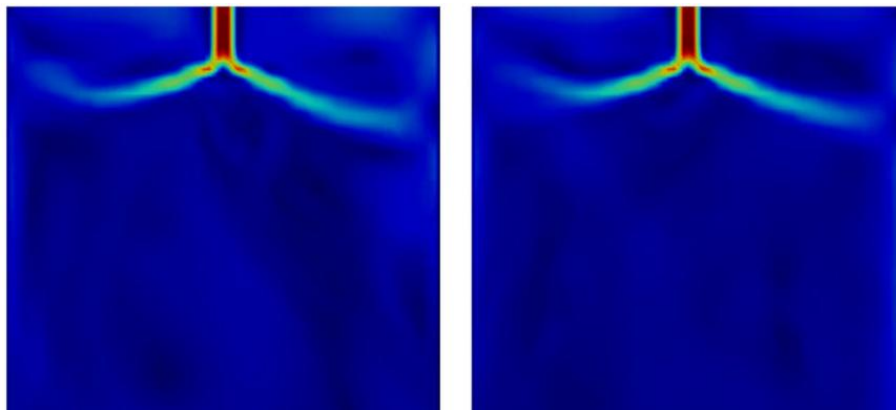


Fig. 3 Snapshots after 10 s real life runtime (corresponds to 100 snapshots). Left. Simulation using the parameters 1.5 m/s casting speed, 1500 mm casting length, 225 mm width, and 160 mm entry nozzle submergence depth. Right. Interpolation using two simulations

Obr. 3 Snímky po 10 sekundách reálného výpočtu (odpovídá 100 snímkům). Vlevo: Simulace s parametry: rychlost lití 1,5 m/s, délka lití 1500 mm, šířka 225 mm a hloubka ponoření vstupní trysky 160 mm. Vpravo: Interpolace na základě dvou simulací

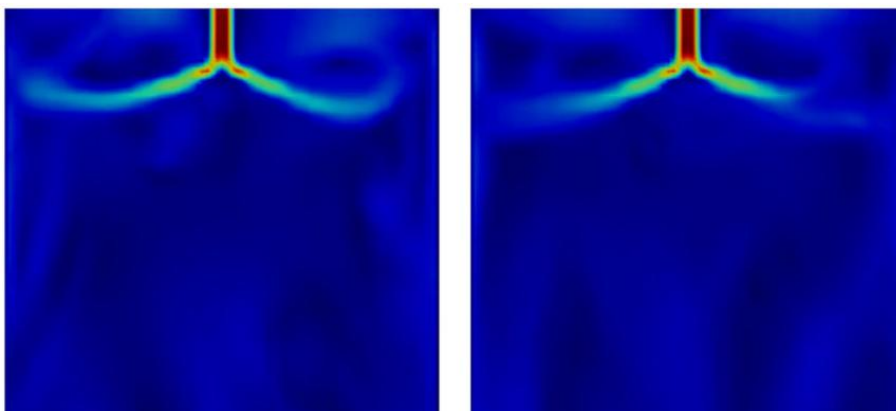


Fig. 4 Same case as in Fig. 2, but after approximately 3 seconds

Obr. 4 Stejný případ jako na obr. 2, avšak po přibližně 3 sekundách

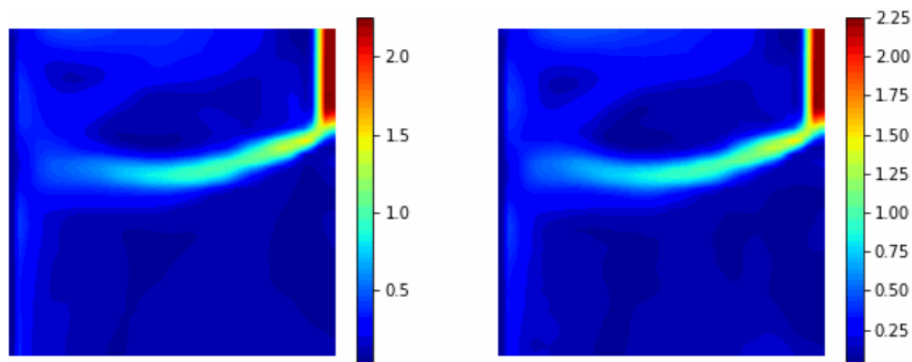


Fig. 5 Snapshots after 3 s real life runtime (corresponds to 30 snapshots). Left. Simulation using the parameters 1.5 m/s casting speed, 1500 mm casting length, 225 mm width, and 190 mm entry nozzle submergence depth. Right. Interpolation, where ConvResNet was

Obr. 5 Snímky po 3 sekundách reálného výpočtu (odpovídá 30 snímkům). Vlevo: Simulace s parametry: rychlost lití 1,5 m/s, délka lití 1500 mm, šířka 225 mm a hloubka ponoření vstupní trysky 190 mm. Vpravo: Interpolace, kde byl použit model ConvResNet

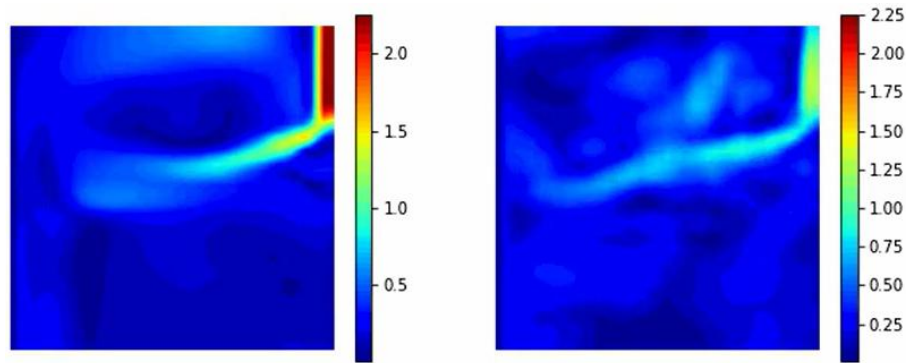


Fig. 6 Same case as in Fig. 4, but after approximately 6 s

Obr. 6 Stejný případ jako na obr. 4, avšak po přibližně 6 sekundách

4. Conclusion and Outlook

- This work presents a hybrid approach combining ROM with ML to accelerate CFD simulations in steel casting. DMD serves as a fast baseline for laminar flows, capturing average flow behavior but often lacking physical accuracy and turbulent structures.
- ConvResNet effectively model nonlinear and transient dynamics across parameter variations in the early stages of simulation, though they suffer from error accumulation over time due to their stepwise prediction structure. While ML-based ROMs offer significant computational speed-ups, challenges remain in modelling fully turbulent flows, scaling to 3D domains, and preserving physical consistency.
- Future work will focus on integrating physics-aware 3D architectures, developing hybrid models that embed PDE knowledge, and applying these tools for real-time control and defect prediction in casting processes.

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