Universität Bremen

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BOSCH

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Fachbereich 03
Mathematik und Informatik

Physics-Informed Neural Networks (PINN) for Injection Moulding

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Introduction:

Partial differential equations (PDEs) are used to simulate many industrial processes; in these cases, costly or even impractical trials can be substituted by numerical simulations. Deep neural networks are used in recent methods to handle PDEs numerically efficiently by approximating solutions or solution operators.
The idea of Physics-Informed Neural Networks (PINN), which minimizes a PDE-based penalty function while a neural network is being trained, is one of these methods.

Injection Moulding:

Injection molding, defined as a cyclic process for producing identical articles from a mold, is the most widely used polymer processing operation.

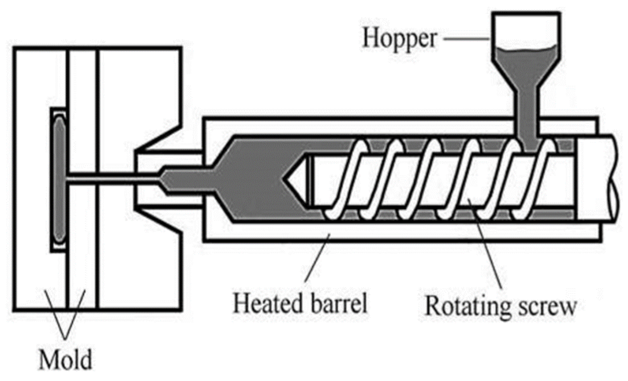


Fig: A sketch of a reciprocating screw injection molding machine.

Governing equations for Injection moulding process:

Volume of Fluid Method:

Relative melt/air properties φ i.e ρ, η dependent on phase fraction α:

$$\varphi = \varphi_m \alpha + \varphi_a(1-\alpha)$$

Propagation of Phase Fraction α via Transport Equation:

$$\frac{\partial \alpha}{\partial t} + V \cdot \nabla \alpha = 0$$

Conservation of Mass for a fluid:

$$\frac{\delta \rho}{\delta t} + \nabla \cdot (\rho V) = 0$$

where,

- ρ is the polymer density
- t is time
- V is the velocity vector

Conservation of Momentum:

$$\rho \frac{DV}{Dt} = -\nabla P + \nabla \cdot \tau + \rho g$$

where,

- $\frac{D}{Dt}$ is the material derivative
- P is pressure
- τ is the viscous stress tensor
- g is the gravitational acceleration vector
- $\tau = \eta(\nabla V + \nabla V^T)$

Reynolds Number:

$$\text{Re} = \frac{\rho u L}{\mu}$$

TorchPhysics:

Is a Python library of (mesh-free) deep learning methods to solve differential equations.

❖ The following approaches are implemented

- Physics-informed neural networks (PINN)
- Q Res
- Deep Ritz methods
- DeepONets
- Physics-Informed DeepONets

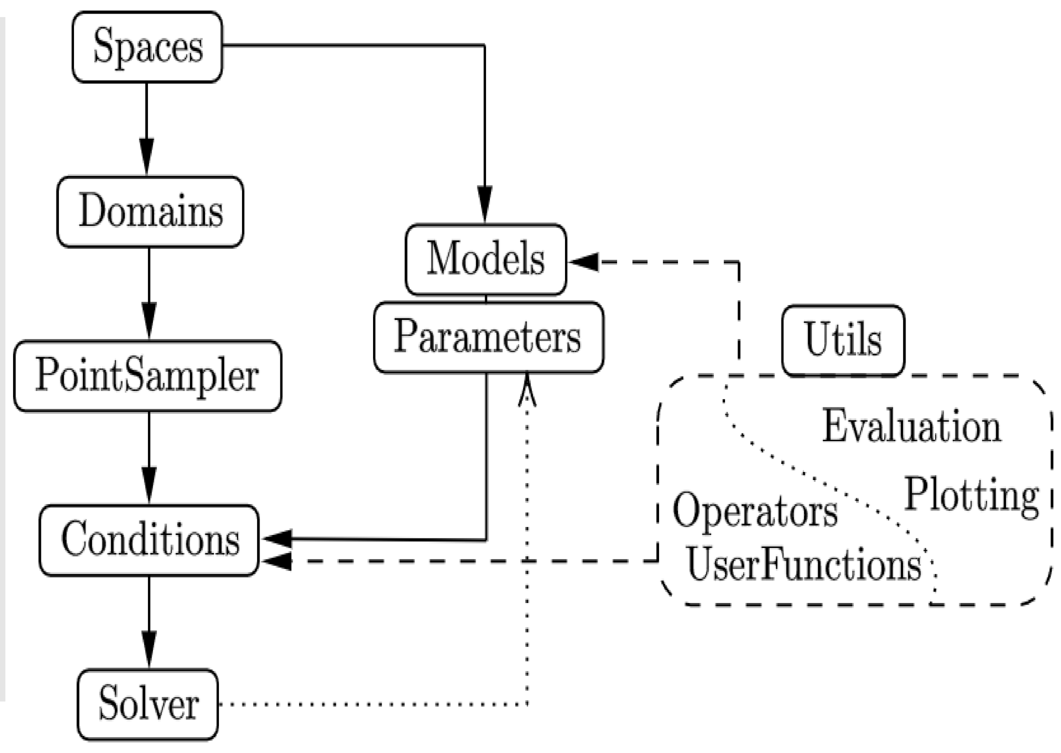


Fig: structure of Torchphysics

PINN:

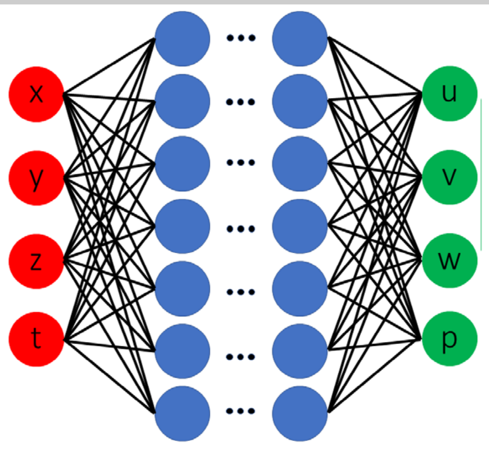


Fig: Physics-informed neural networks for solving Navier-stokes equations

Navier stokes loss

$$V = (u, v, w)$$
$$\partial_t V + (V \cdot \nabla)V = -\nabla p + \mu \Delta V$$
$$\nabla \cdot V = 0$$

Experimental Data loss

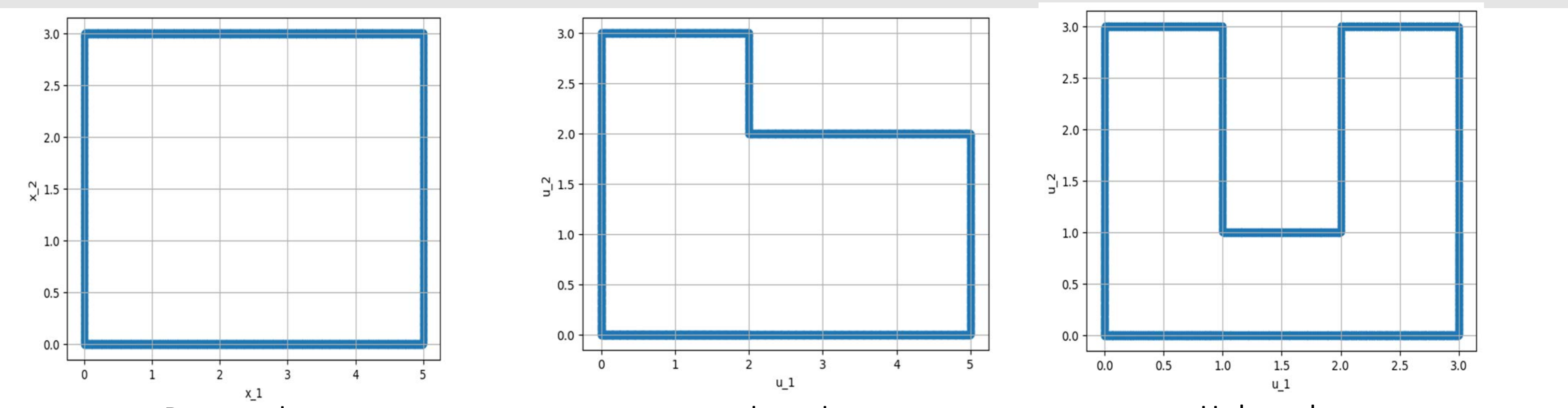
$$\|V - V_{exp}\|^2 = 0$$

Definition and Key Ingredients:

Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations.
1st key ingredient → Availability of gradients y1 , y2, etc. with respect to input 'x'
2nd key ingredient → Loss function, or constructing a custom L(θ)
3rd key ingredient → Leveraging NN learning algorithm

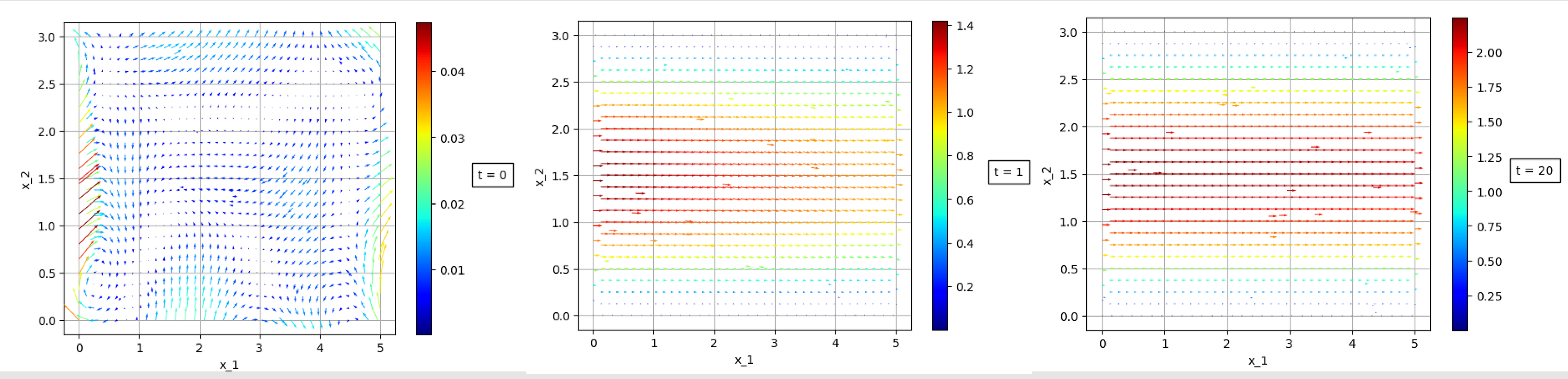
Results using TorchPhysics library:

Creating Geometry : Domains handle the geometries of the underlying problems

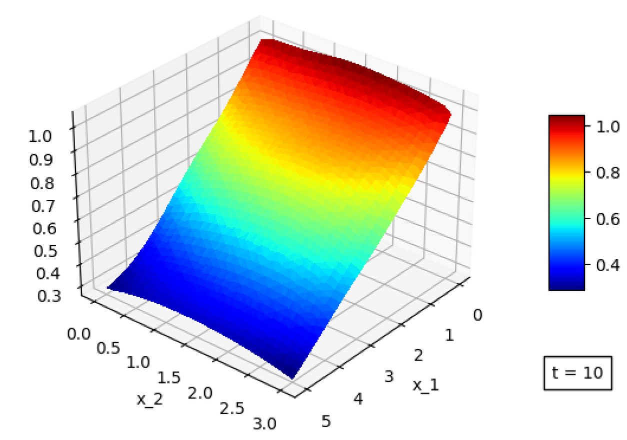


Rectangular   L shaped   U shaped

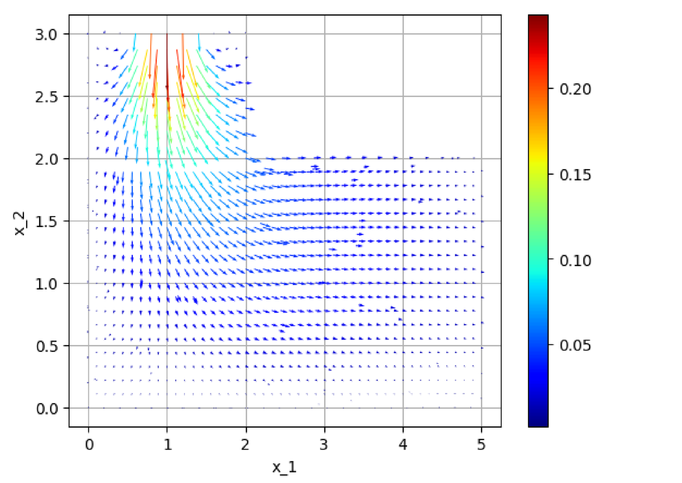
Rectangular Domain with different time constraint :



Implementation of transport residual:



Plot Sampler for alpha with 10000 training steps, along with time constraint, transport sampler points = 10000



L shaped domain without time constraint for 50000 training steps, with Adam optimizer

References :
1.TorchPhysics, https://torchphysics.readthedocs.io/en/latest/index.html
2.Boschresearch https://github.com/boschresearch/torchphysics
3. Injection Molding: Integration of Theory and Modeling Methods | SpringerLink

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