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PHYSICS-INFORMED MANUFACTURING: PINNs FOR HYDROFORMING PROCESS MODELLING

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ABSTRACT

Physics-Informed Neural Networks, PINNs in short, are a novel class of deep learning models embedding the governing, physics-based laws into training the neural network. This hybrid approach enables accurate solutions to forward and inverse problems in scientific computing, especially in areas where data is scarce or costly. In the context of manufacturing, PINNs have shown growing promise in modelling complex phenomena in metal forming processes, including elasticity, plasticity, and large deformation behaviour. This paper provides a review of PINN architecture, it's integration into metal forming, with a focus on hydroforming, which is highly sensitive to material flow and boundary conditions. Relevant case studies are discussed, highlighting the capabilities of PINNs in stress-strain prediction, optimization and coupling. Lastly, the review outlines the current challenges and future opportunities for applying PINNs to develop data-efficient, physics-based, and scalable models in advanced manufacturing.

Keywords: *Physics-Informed Neural Networks, Hydroforming, Metal Forming, Plasticity, Optimization*

NOMENCLATURE

$L(\theta)$	Total loss function of the PINN (dimensionless)
L_{BC}	Loss term for boundary condition constraints (dimensionless)
L_{data}	Data loss component (difference between predicted and observed values) (dimensionless)
L_{PDE}	PDE loss component (residuals of governing equations) (dimensionless)
T	Final time (s)
t	Temporal coordinate (s)
$u(x,t)$	Unknown solution variable (m)
$u_{\{\theta\}}(x,t)$	Neural network approximation of the solution, having θ as parameter (m)
x	Spatial coordinate (m)
Greek Symbols	
θ	weights and biases of the neural network (dimensionless)
Ω	Spatial domain (m^3)
Operators	
$\mathcal{N}[\cdot]$	General differential operator (dimensionless)

1. INTRODUCTION

Hydroforming is a critical manufacturing process widely used for producing lightweight and high-strength components, particularly in the automotive, aerospace, and biomedical industries [1]. The process involves forming ductile metals into desired shapes using a high-pressure hydraulic fluid, which allows for complex geometries and reduced material waste [2]. However, accurately modelling hydroforming presents several challenges due to its inherently nonlinear nature, involving fluid-structure interaction, contact phenomena, and material plasticity. Traditional numerical methods, such as the finite element method (FEM) have been extensively used to model the hydroforming processes [3, 4]. While FEM offers high accuracy, it often requires fine meshing, high computational cost, and manual tuning of boundary conditions and material parameters. Moreover, FEM struggles with inverse problems and real-time control applications, which are increasingly essential in modern manufacturing.

PINNs, a novel class of machine learning techniques, embed the governing physics, primarily as partial differential equations, into the training procedure directly. Unlike the neural networks which are used conventionally and are data-driven, PINNs do not rely only on labelled data, but also learn from the equations representing the system and boundary conditions as well. And for that matter it produces mesh-free, data-efficient, and generalizable solutions for complex physical systems. This review aims to understand the work done in PINNs, go over a few of its applications, although focusing on manufacturing, so that it can be used in hydroforming simulations, focusing on recent advances in network architectures, training, and case studies. The paper also highlights the current limitations and research opportunities in integrating PINNs into digital manufacturing workflows for process optimization and control.