

# A SIMULATION-DATA-BASED MACHINE LEARNING MODEL FOR QUALITY PREDICTION OF CONSOLIDATED THERMOPLASTIC PARTS

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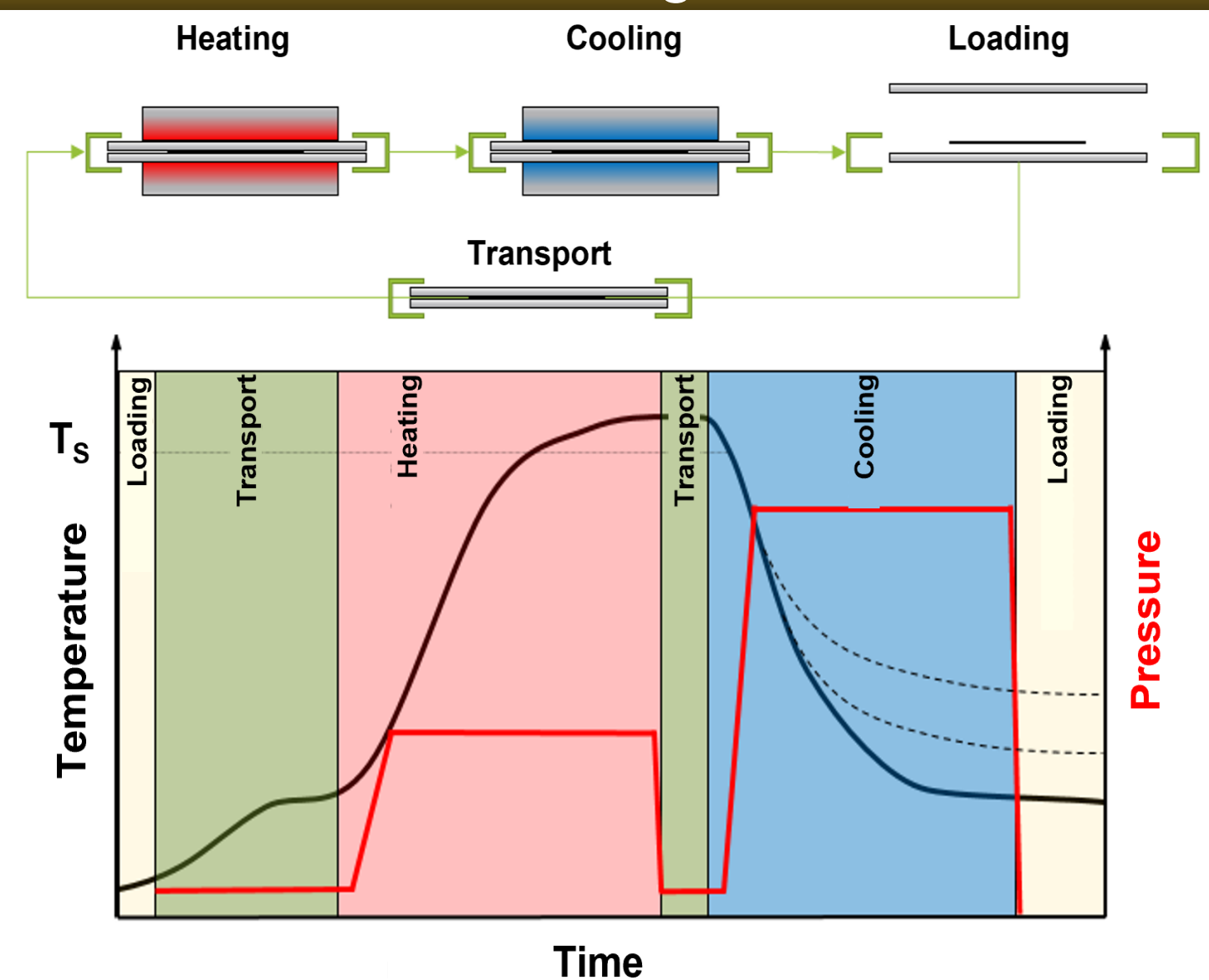
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## Introduction

**Fibre-reinforced thermoplastic composites** have become increasingly popular for lightweight applications due to their excellent mechanical properties and potential for recycling. These composites are based on **unidirectional (UD) tapes**, which can be easily processed into complex shapes using automated manufacturing techniques. An important step in the manufacturing of components from these tapes is **consolidation**, which involves heating and pressing several layers of the tape together to fuse them into a single piece. The **optimization** of novel manufacturing processes in industrial contexts can be challenging due to the time and cost constraints of experimental approaches. To overcome this challenge, computational approaches have emerged as a cost-effective and efficient solution. A typical workflow consists of (a) the replacement of systematic experimentation by **physical modeling**, creating artificial data for (b) the subsequent replacement of computationally expensive physical models by **fast surrogate (non-parametric) models**, and (c) the calibration of the surrogate models by **experimental observation**. In this study, we use the ground truth generated by a computational fluid dynamic (CFD) model to train a surrogate fast neural network (NN) which was subsequently **calibrated to experimental data**.

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## Manufacturing Process



## Data

### Input Data

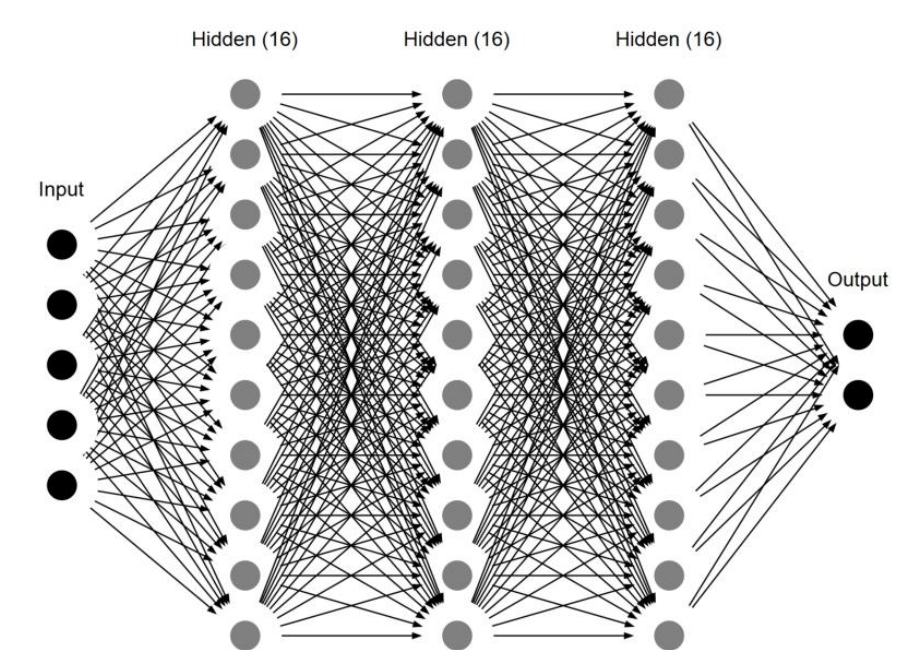
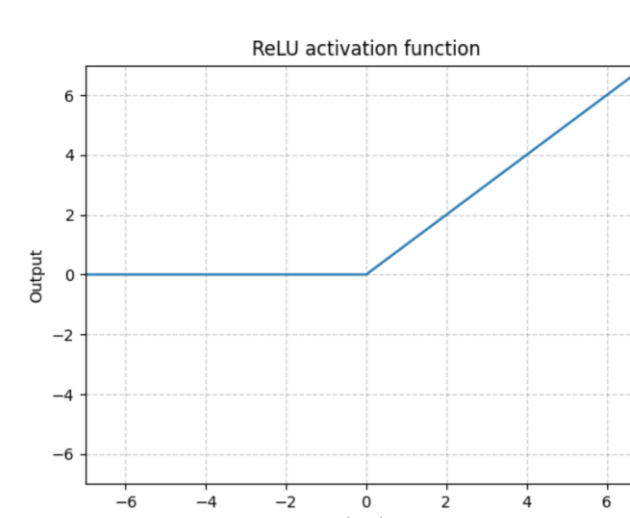
	Low setting	Mid setting	High setting	Lower Bound	Upper Bound
Hot Press Temperature	473.15 K	523.15 K	573.15 K	473.15 K	623.15 K
Hot Press pressure	100000 Pa	300000 Pa	500000 Pa	50000 Pa	800000 Pa
Cold Press Temperature	333.15 K	373.15 K	413.15 K	313.15 K	413.15 K
Cold Press pressure	1000000 Pa	2000000 Pa	3000000 Pa	1000000 Pa	9000000 Pa
Holding Time/Cycle Time	5 s	10 s	15 s	0 s	500 s

### Output Data

- Degree of Bonding (DoB)
- Displacement (relative change of thickness)

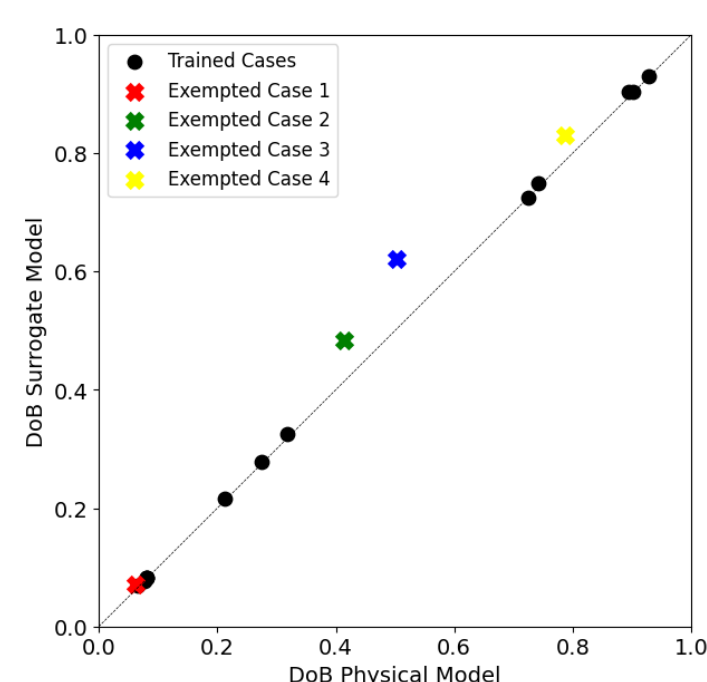
## Network Architecture

Hidden Layers	3
Nodes per Hidden Layer	16
Activation Function	ReLU



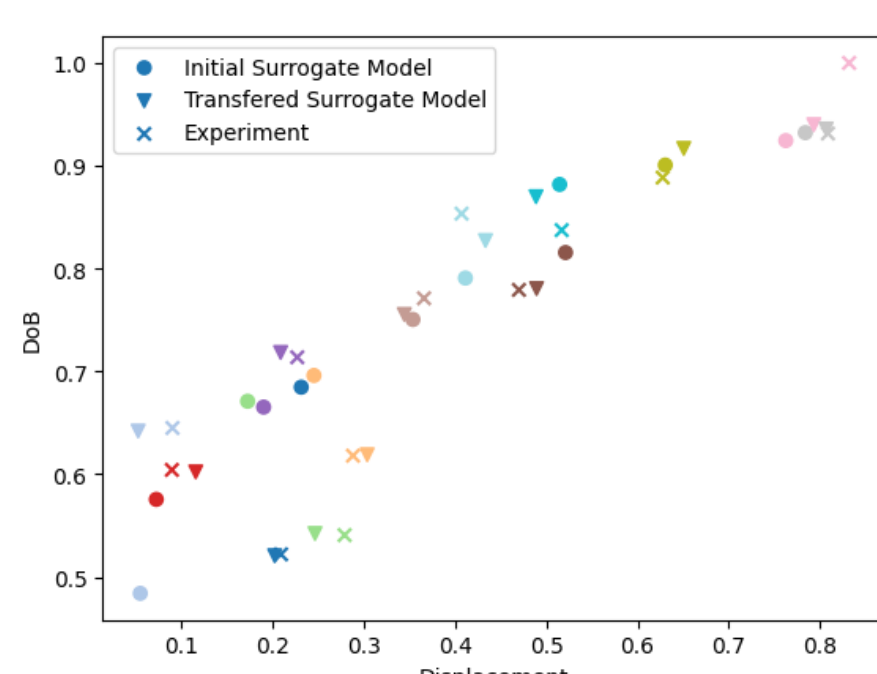
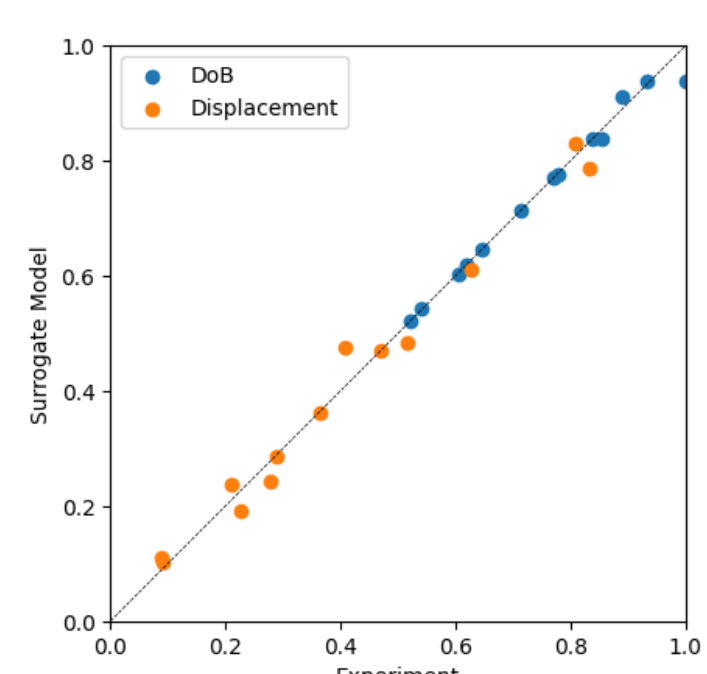
## Results

### Initial Learning



Exempted Case Number	MSE
1	$7.57 \cdot 10^{-5}$
2	$5.05 \cdot 10^{-3}$
3	$1.37 \cdot 10^{-2}$
4	$1.75 \cdot 10^{-3}$

### Transfer Learning



## Conclusion

We used a neural network as a **universal function approximator** to predict the complex time dependence of specific parameters of the consolidation process. It was possible to obtain an accurate and robust model based on a **few process points**.

The NN can fundamentally use **endpoints only** to predict the outcome. While NN will necessarily pick up systematic inconsistencies or inaccuracies inherent to the physical model, data-driven models confer the advantage that they can be **corrected by a transfer learning step**.

We have investigated several transfer approaches by using the ILSS, and tape thickness.

The presented workflow permits the **prediction of quality parameters** from process settings within seconds, enabling efficient process optimization and control.

This hybrid approach thus provides a cost-effective and efficient solution for optimizing the consolidation step of the **composite manufacturing chain**.

## Acknowledgments

The authors acknowledge financial support through the COMET Centre CHASE, funded within the COMET - Competence Centers for Excellent Technologies programme (No. 868615) by the BMK, the BMDW and the Federal Provinces of Upper Austria and Vienna. The COMET programme is managed by the Austrian Research Promotion Agency (FFG).