PREDICTING HEAT TRANSFER COEFFICIENT USING BIDIRECTIONAL LONG SHORT-TERM MEMORY

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INTRODUCTION

THE HEAT TRANSFER PROBLEM

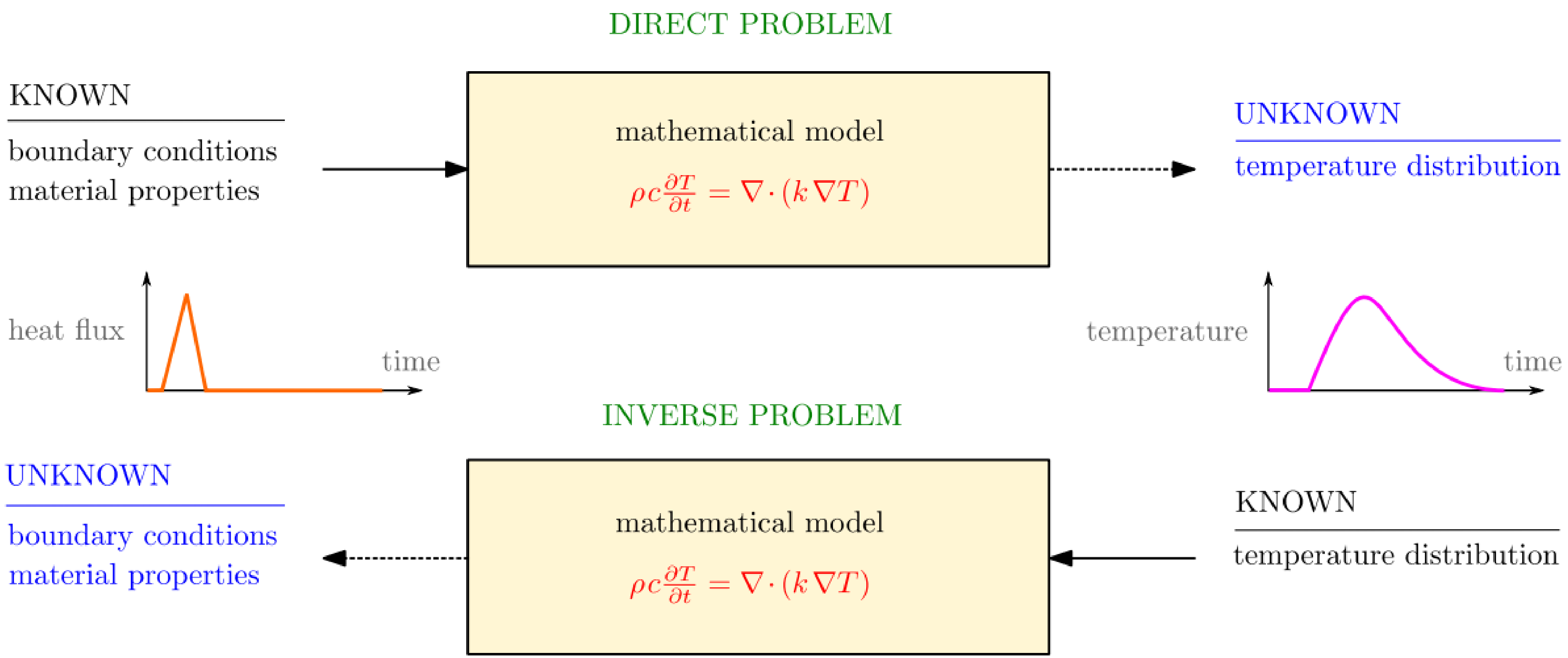
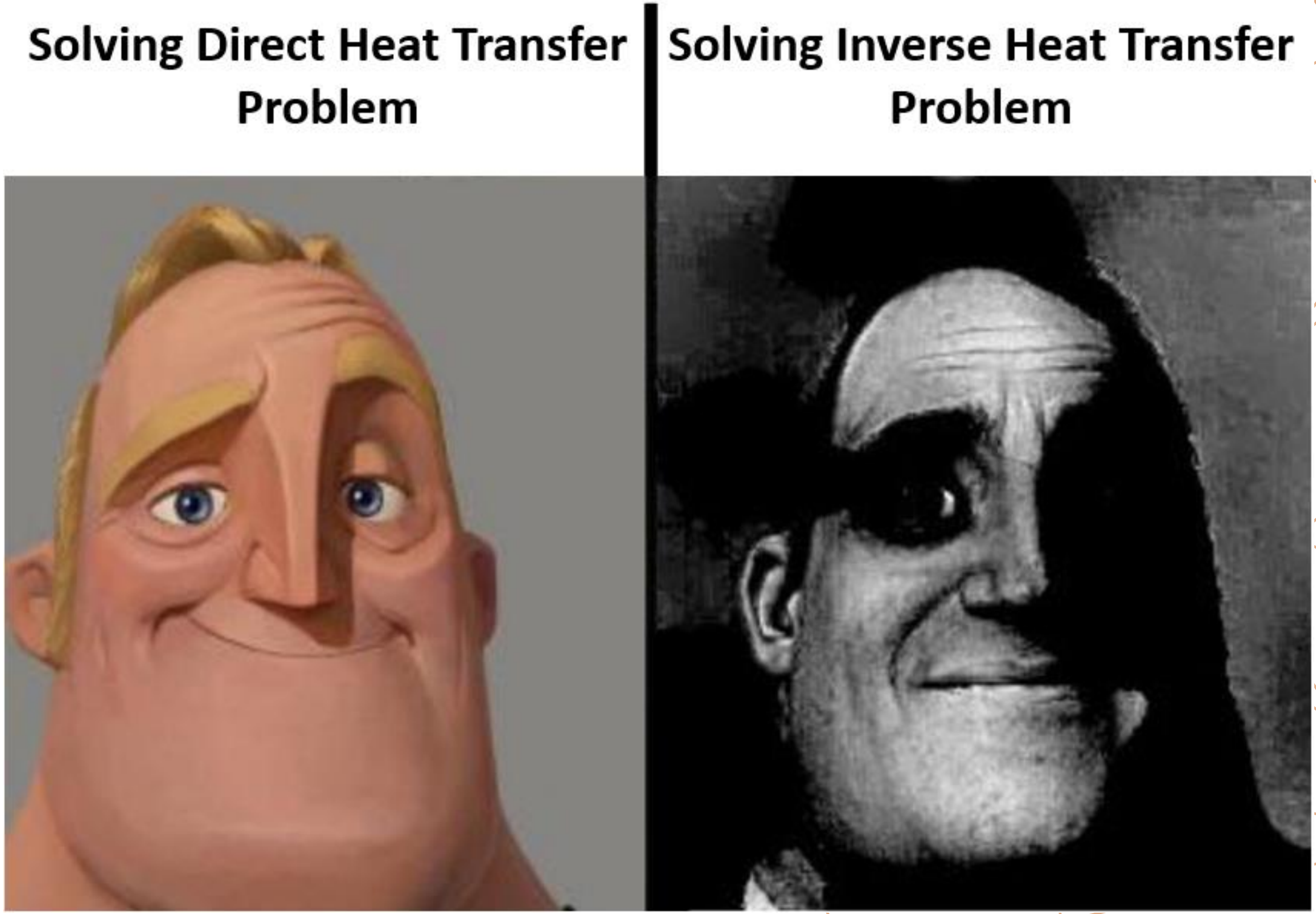


FIG. The Direct and Inverse Heat Transfer Problem (IHTP) [1]


Solving Direct Heat Transfer Problem
Solving Inverse Heat Transfer Problem

WHY IS IT DIFFICULT TO SOLVE IHTP?

- Non-uniqueness of the solution
- Ill-posed
- Complex nature of physical systems
- Nonlinearities
- Limited observations, etc.

WHAT IS HTC?

- Heat Transfer Coefficient is the proportionality constant between the heat flux and temperature difference
- Used in calculating the heat transfer, typically by convection or phase transition between a fluid and a solid
- Prediction of HTC from Temperature data -> IHTP

WHY IS KNOWLEDGE OF HTC IMPORTANT?

- Controlling cooling rates to achieve desired microstructural properties [2, 3]
- Improving energy efficiency
- Optimization of thermal performance

DIFFERENT METHODS APPLIED TO SOLVE IHTP

- Iterative and gradient-based
- Meta-Heuristic (e.g. PSO, genetic algorithm) [4 - 9]
- Machine Learning [10 - 12]

METHODOLOGY

AIM — To see the ability of Neural networks to solve the IHTP (prediction of Heat Transfer Coefficient)

MODELS — Different Neural networks (FFNN, RNN, LSTM, BiLSTM) compared

DATA SET — Obtained from Szénási and Felde [12]

METHODOLOGY

DATASET OVERVIEW

DATA

Dataset composed of information of quenching process (from 850 °C to room temperature) of a cylindrical Inconel 600 bar.

TRAINING

Training set of 1 million datapoints

VALIDATION

Validation set of 100,000 datapoints

TESTING

Testing set of 100,000 datapoints

DATASET OVERVIEW

- INPUT

  Temperature recorded for 1 min at interval of 0.5s

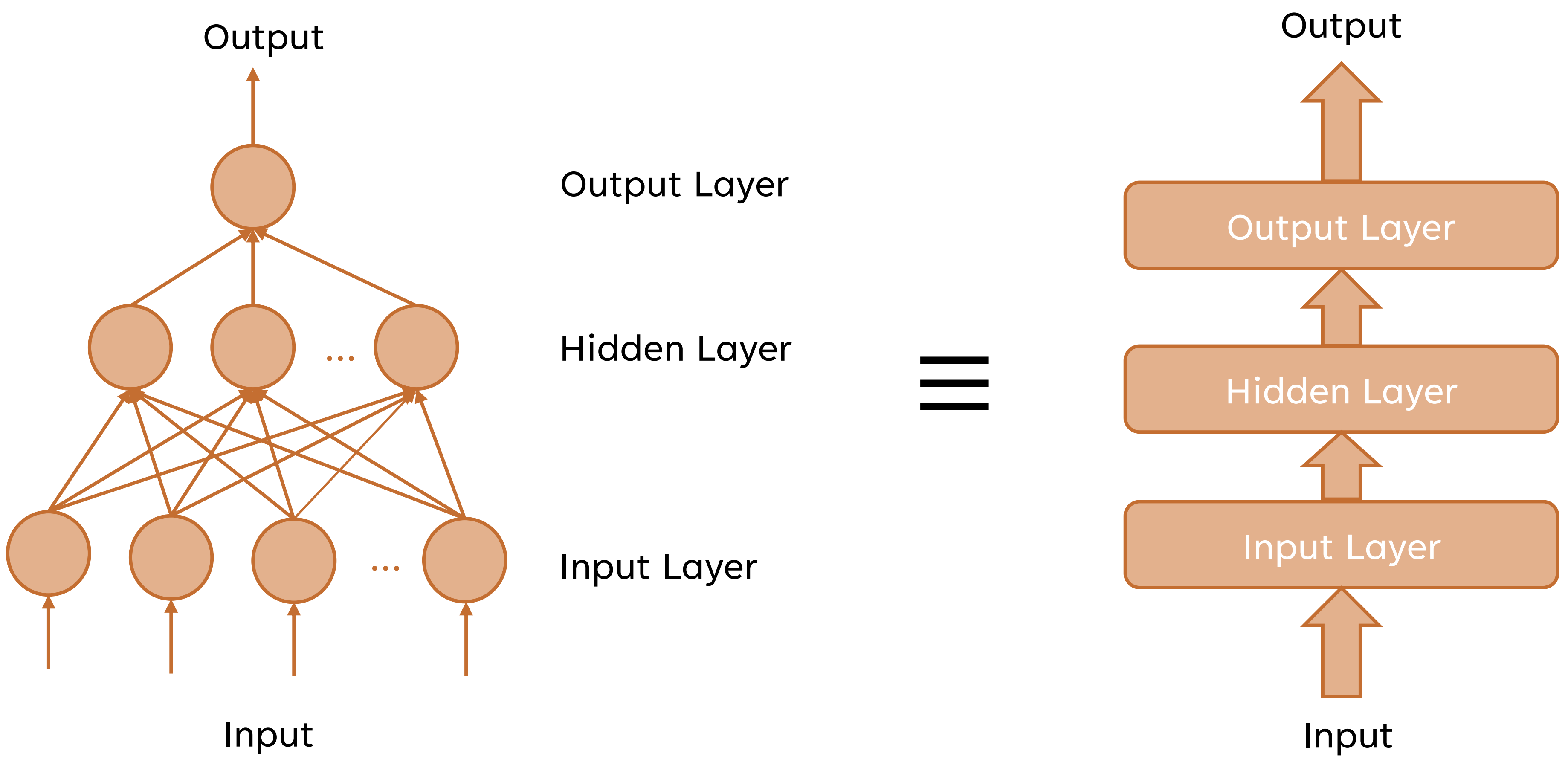
t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	…	t_{120}

- OUTPUT

  HTC at each temperature data point

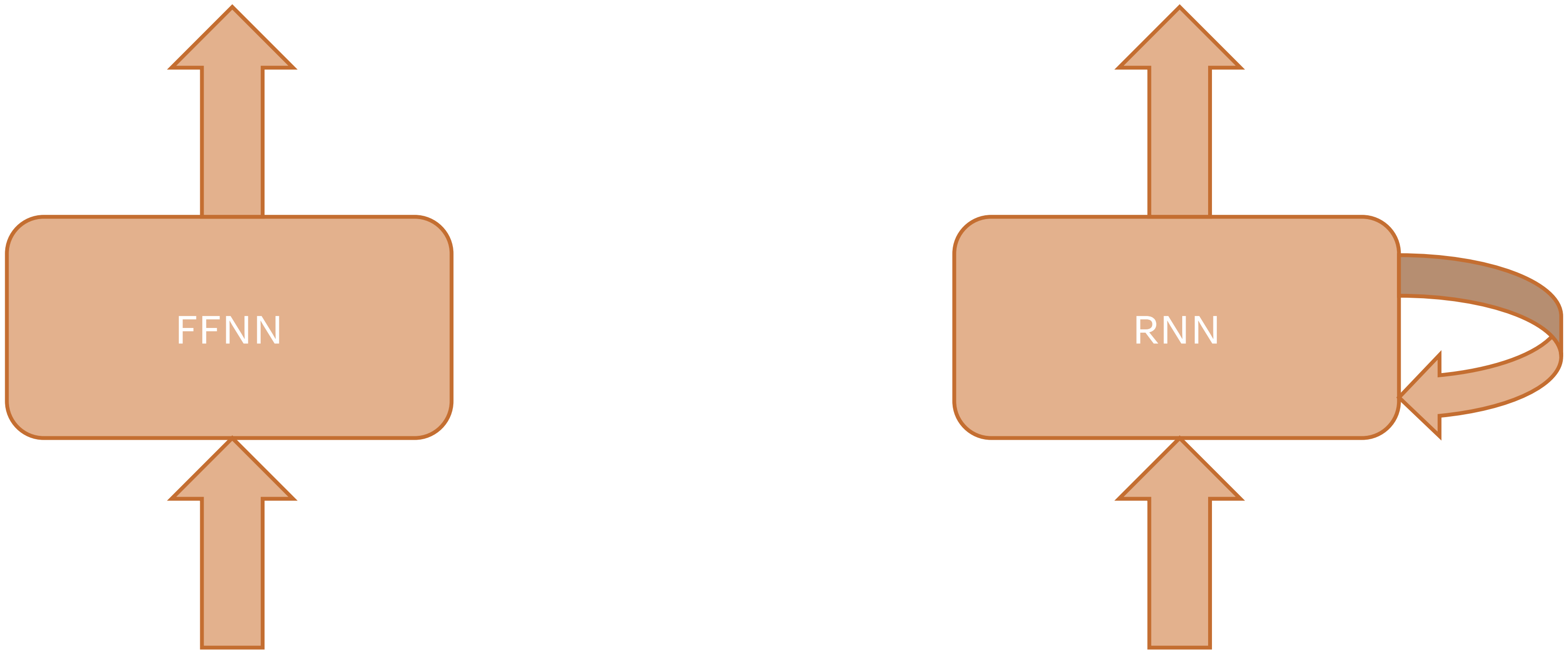
h_1	h_2	h_3	h_4	h_5	h_6	h_7	h_8	…	h_{120}

MODELS USED



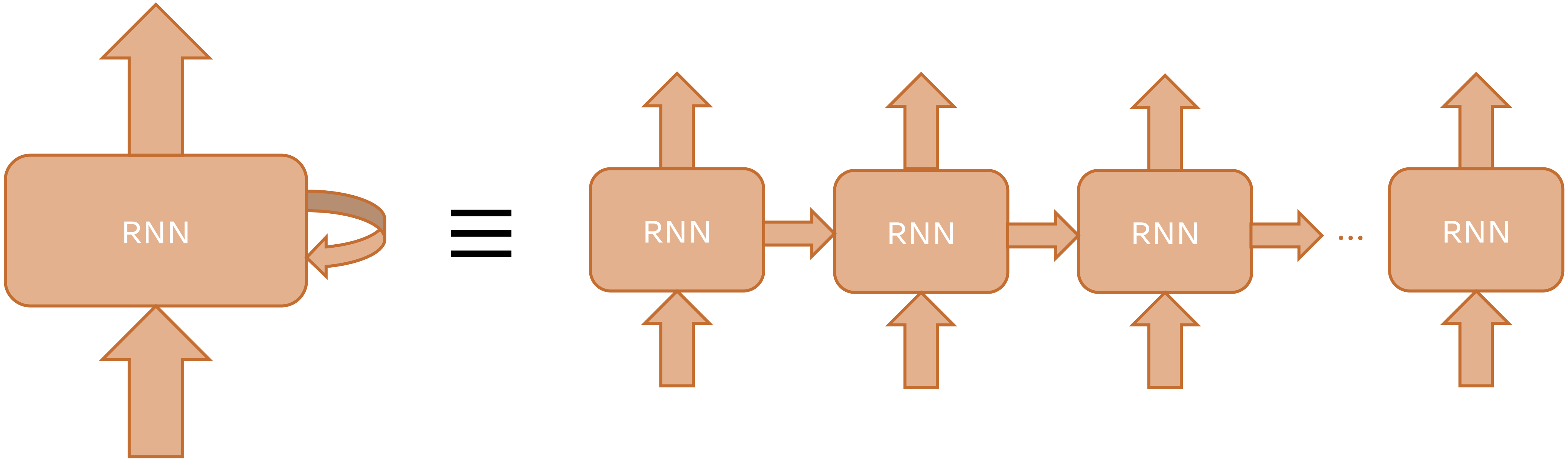
THE FEED FORWARD NEURAL NETWORK (FFNN)

MODELS USED



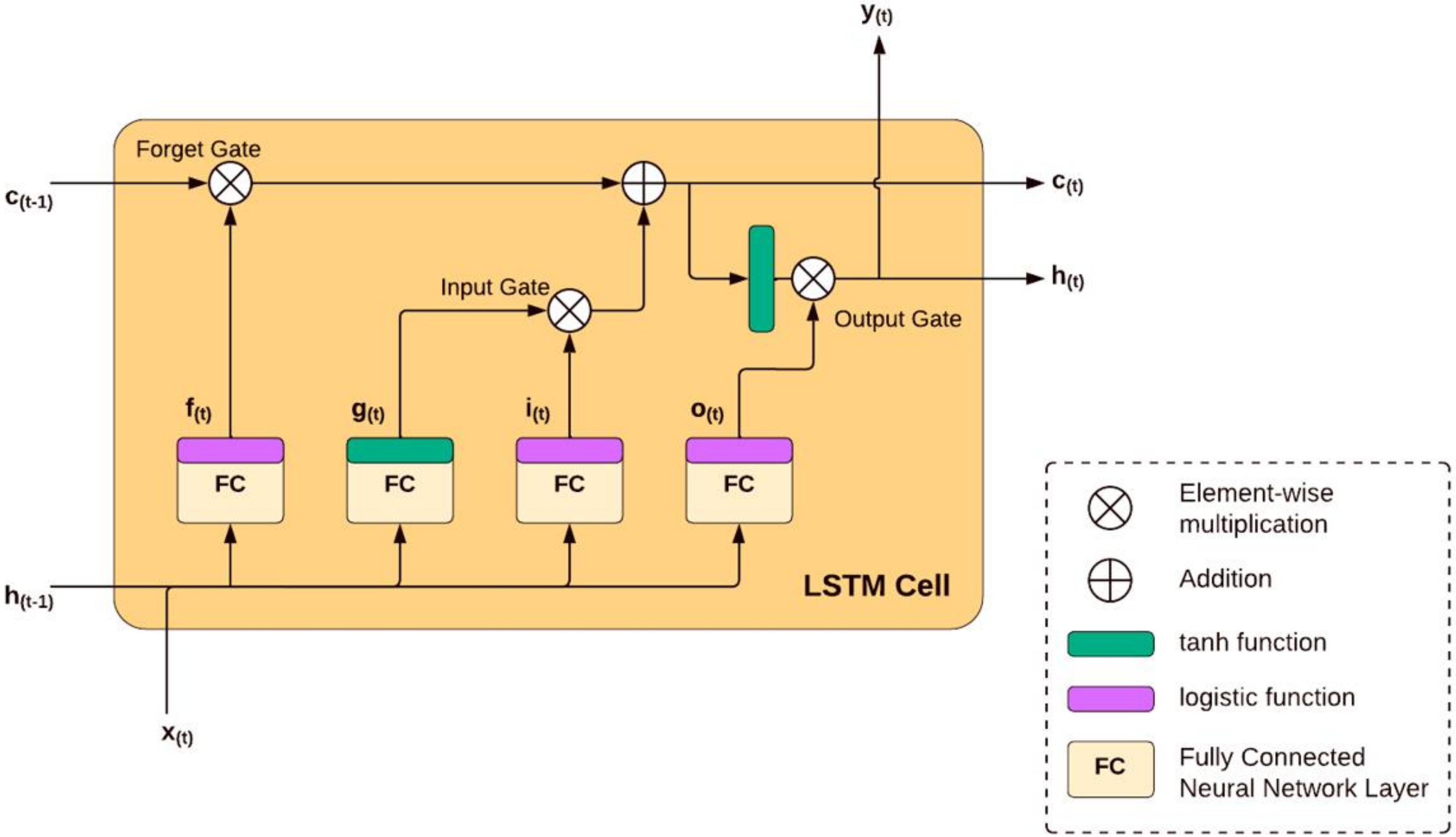
THE RECURRENT NEURAL NETWORK (RNN)

MODELS USED



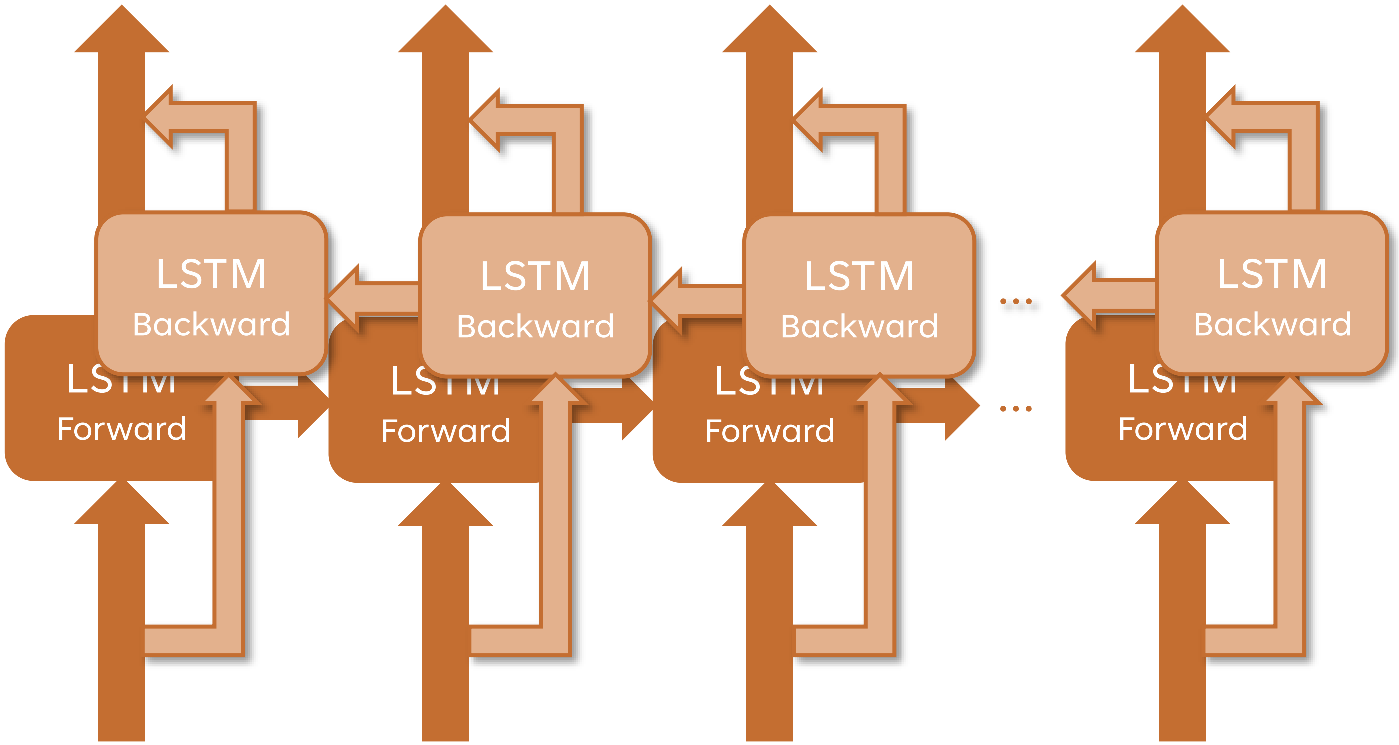
RNN unrolled through time

MODELS USED



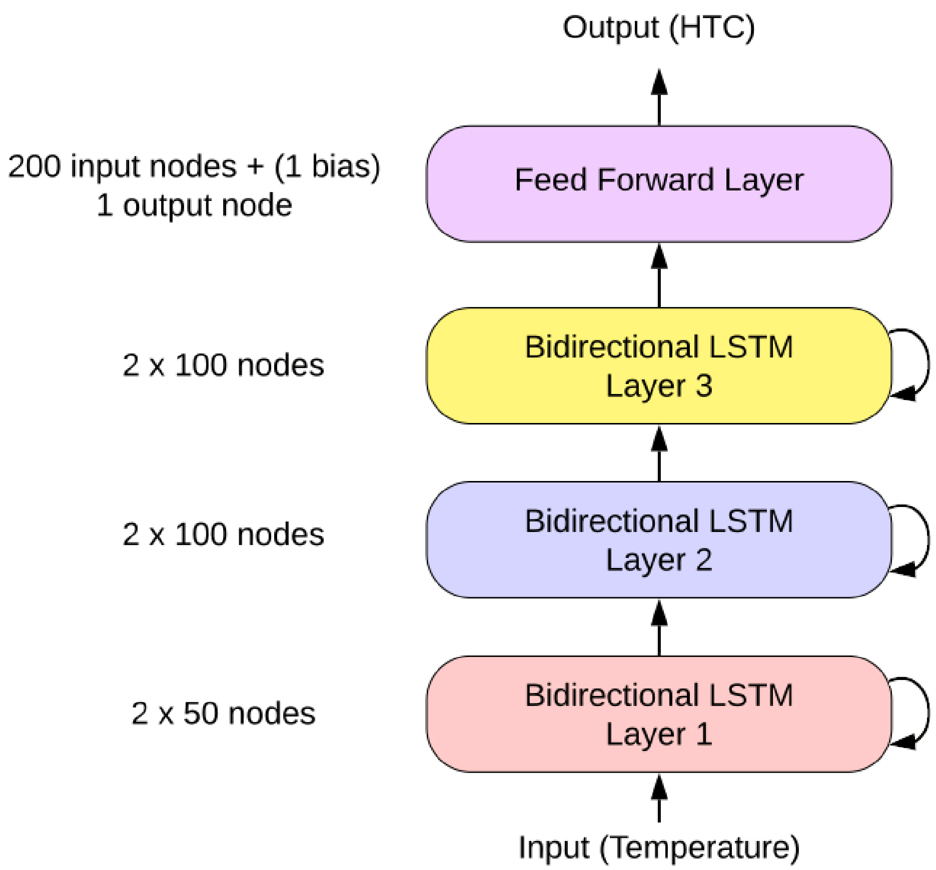
THE LONG SHORT TERM MEMORY (LSTM)

MODELS USED



THE BIDERCTIONAL LONG SHORT TERM MEMORY (BiLSTM)

MODELS USED



THE BiLSTM BASED MODEL WITH BEST PERFORMANCE

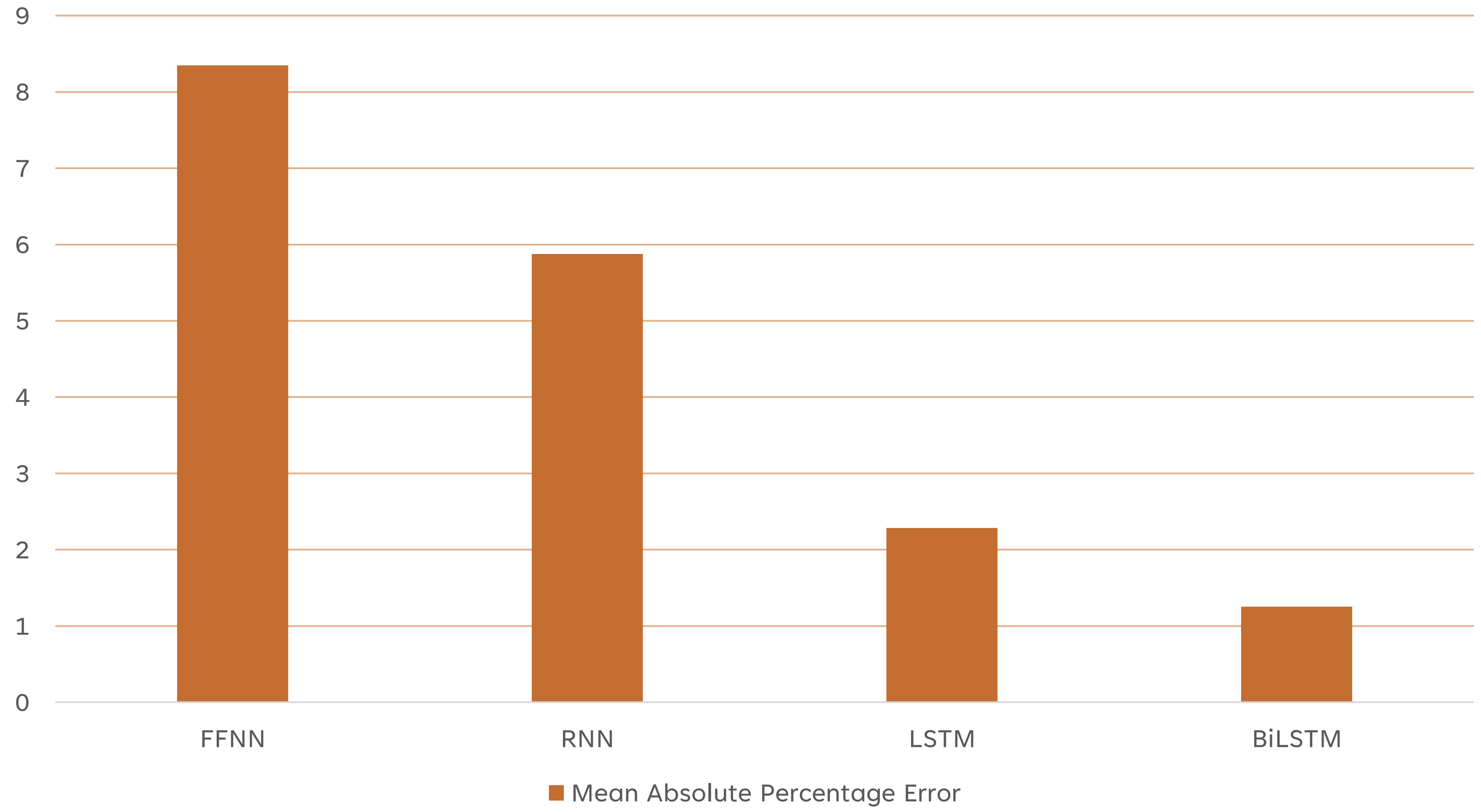
RESULTS AND DISCUSSION

RESULTS

TABLE: Mean Absolute Percentage Errors for the Different Models

Model	Training	Validation	Testing
FFNN	8.3559	8.3646	8.3485
RNN	5.8751	5.8810	5.8768
LSTM	2.2860	2.2847	2.2860
BiLSTM	1.2529	1.2572	1.2548

Mean Absolute Percentage Error of Different Models (on Testing Data Set)



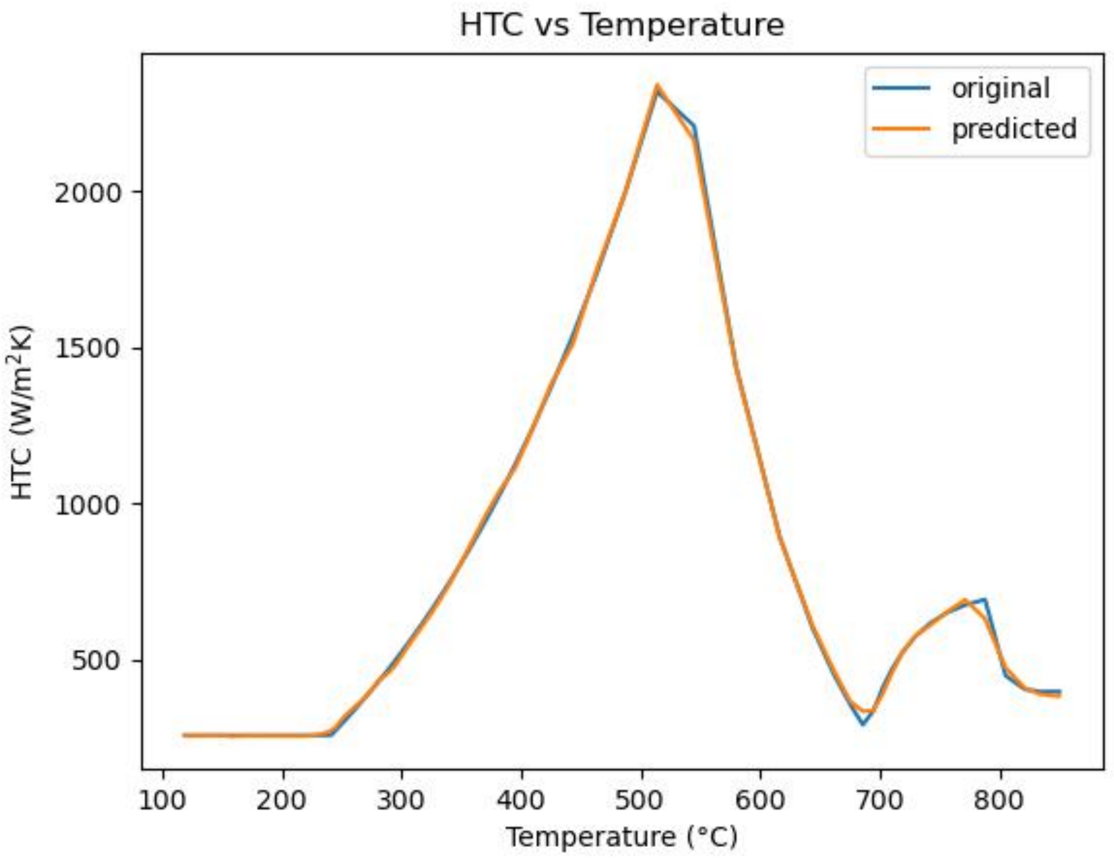


FIG.: HTC vs Temp Plot from BiLSTM model

CONCLUSION AND FUTURE SCOPE

CONCLUSIONS

- BiLSTM outperformed other models.
  - Due to capability to capture temporal relationships.
  - Ability to derive context from both past and future.
- BiLSTM can solve IHTP with sufficient accuracy

FUTURE SCOPE

- Can be generalised using data from different materials
- Other Neural Network architectures can be explored
- Investigating more complex Heat Transfer scenarios

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THANK YOU