33rd Annual INCOSE international symposium

hybrid event

Honolulu HI USA

Physics-Informed Gas Lifting Oil Well Modelling using Neural Ordinary Differential Equations

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Outline

1. Introduction
2. Methodology
3. Result
4. Discussion & Conclusion

Introduction

Why do we need Modelling ?

Describe an engineering system

and benefit multiple applications

Prediction

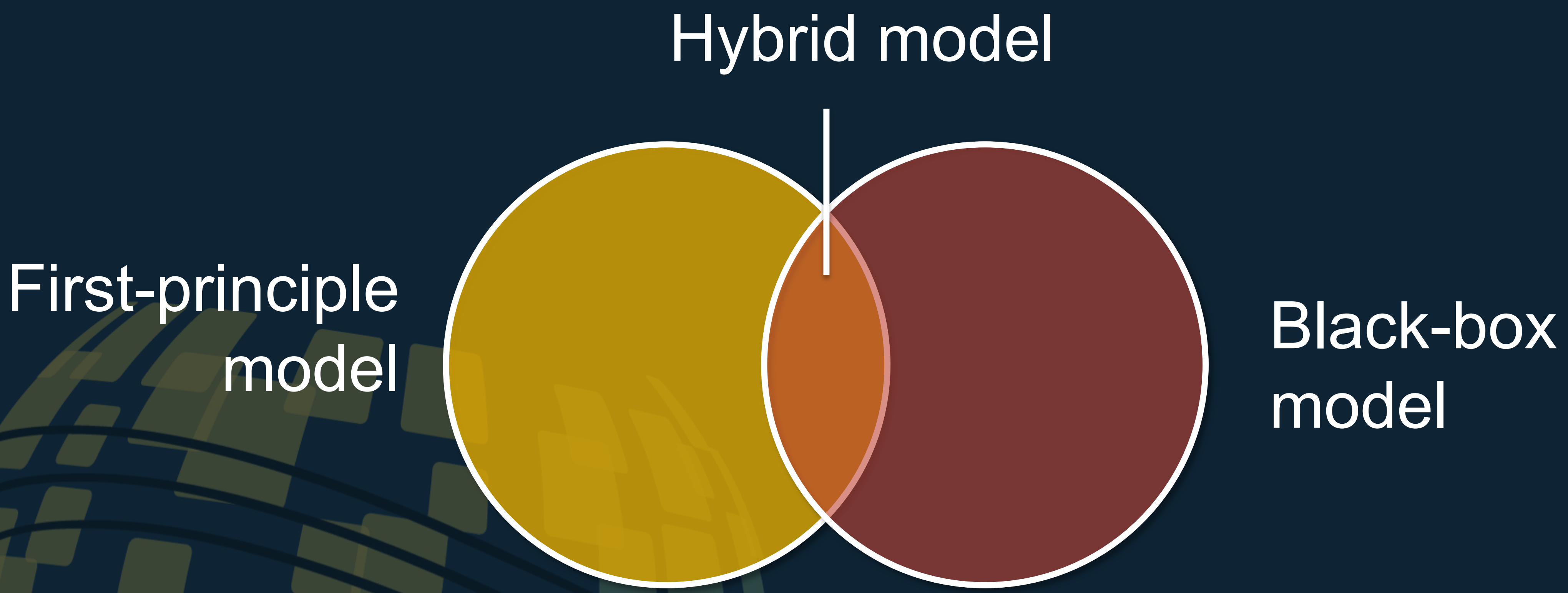
Maintenance

Optimization

Model-based control

Estimation of outputs

Modelling methods



Brief introduction

Goal: Combine data-driven methods and physical knowledge to improve the prediction of oil well dynamics.

Method: physics-informed neural network (PINN)

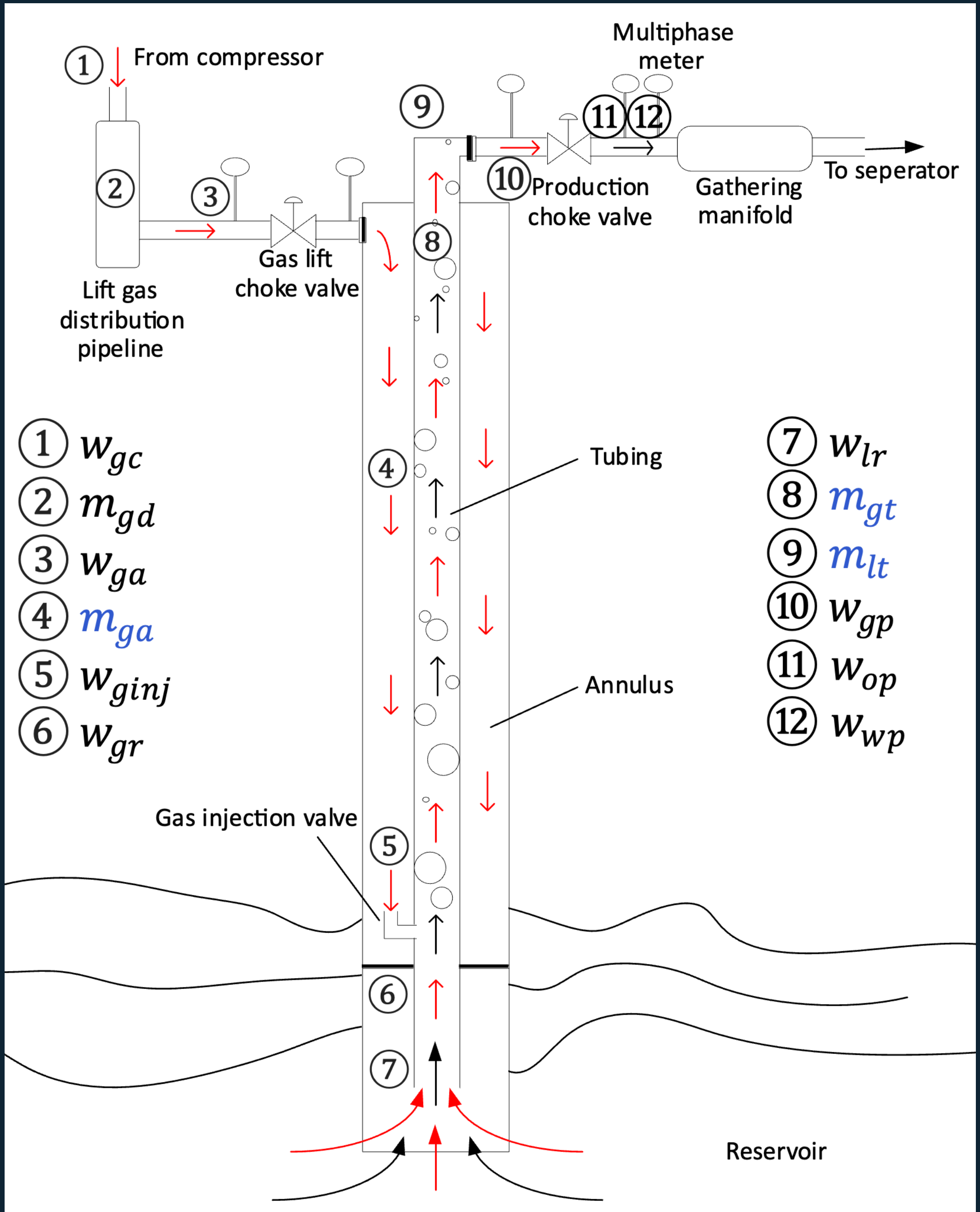
Tool: The neural ordinary differential equation is the main tool for the modeling and the simulation.

Programming language: Julia

Gas Lifting Oil Well

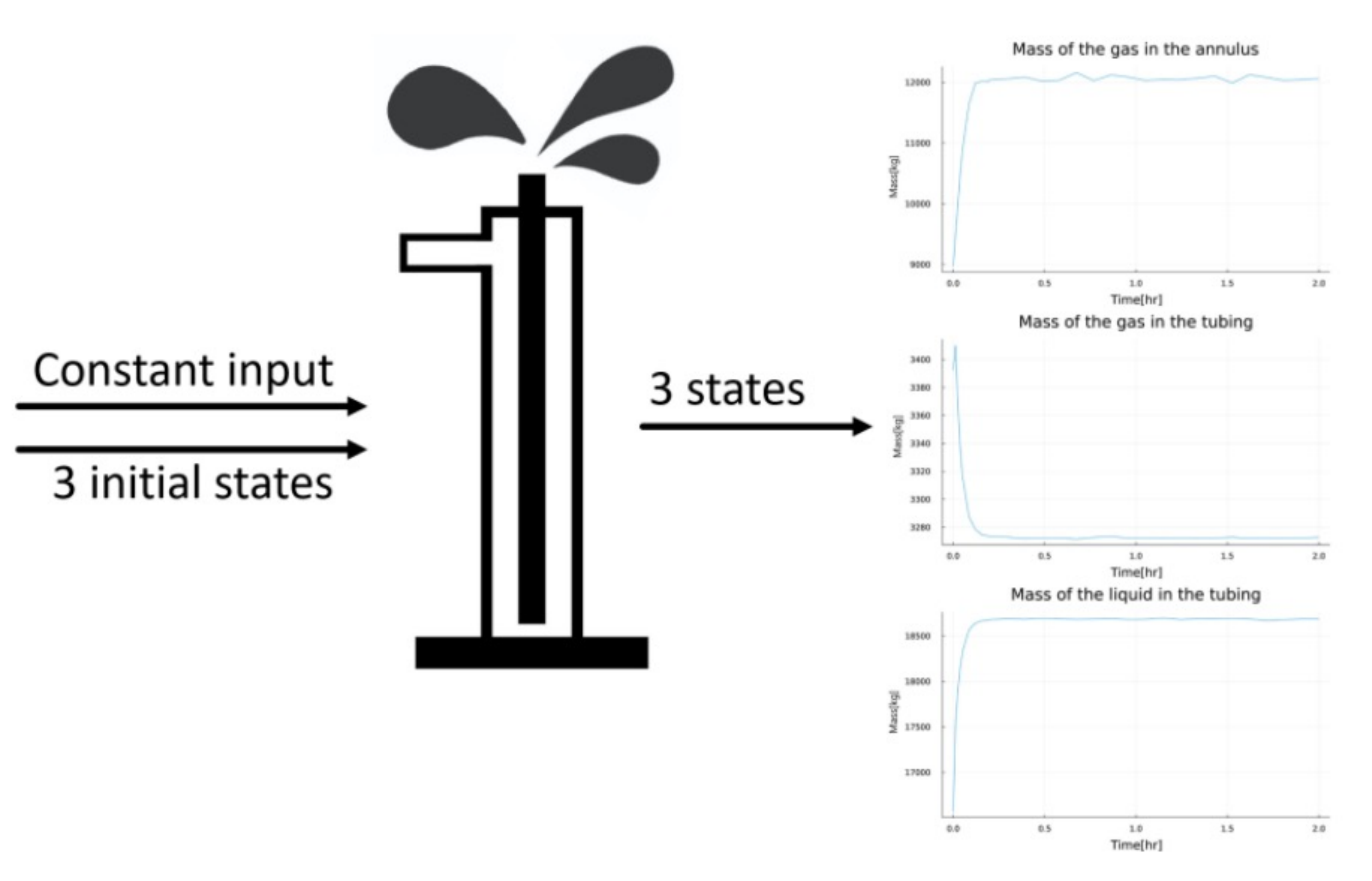
m mass

w flow rate



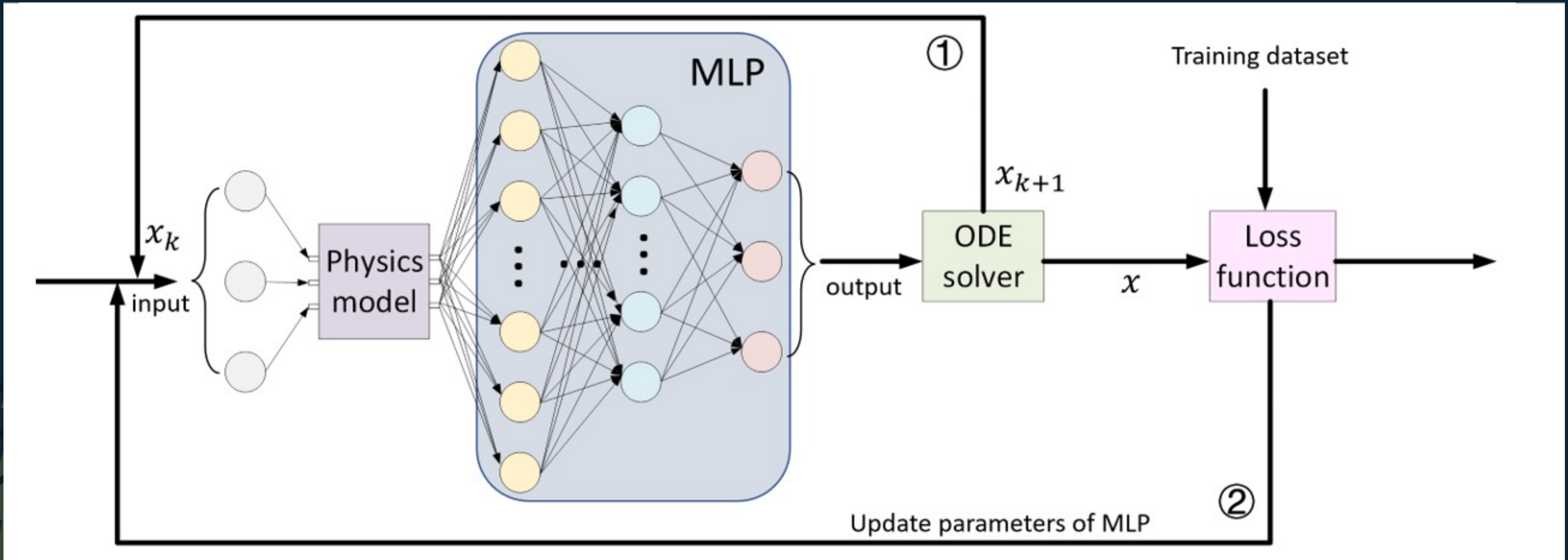
Gas Lifting Oil Well simulator

Parameters: [PI, GRO, WC]
Input: u
States: m_{ga}, m_{gt}, m_{lt}



Methodology

Physics-informed neural network (PINN) model



A physics-informed neural network

- The input of the physics model is the current state vector and control input u.
- The output of the physics model is the derivatives of the state vector, which is then broadcasted to multiple dense layers.
- An ODE solver differentiate the output of the MLP as the prediction of the states at the next time step.

$$\dot{x} = f(x, u)$$

$$PINN(x_k, t_{k+1}) = \int \frac{d\hat{x}_{k+1}}{dt} = \int NN(f(x_k, t_k), t_{k+1})$$

A physics model

$$\dot{m}_{ga} = w_{ga} - w_{ginj}$$

$$\dot{m}_{gt} = w_{ginj} + w_{gr} - w_{gp}$$

$$\dot{m}_{lt} = w_{lr} - w_{lp}$$

+ 23 algebra equations

A physics model

- The simplified physics model provides not only the state estimation at the next time step by solving the ODEs, but also the constraints including prior knowledge of the initial states and input, u.
- The true values of the three parameters in the oil well model were assumed unknown.
- The physical model used here is not necessary to be accurate to describe the whole system. The unknown part and uncertainty can be learnt during the training of the PINN model using training data

Neural Network design

- A neural network is designed to learn the different between the output of the physics model and the training data

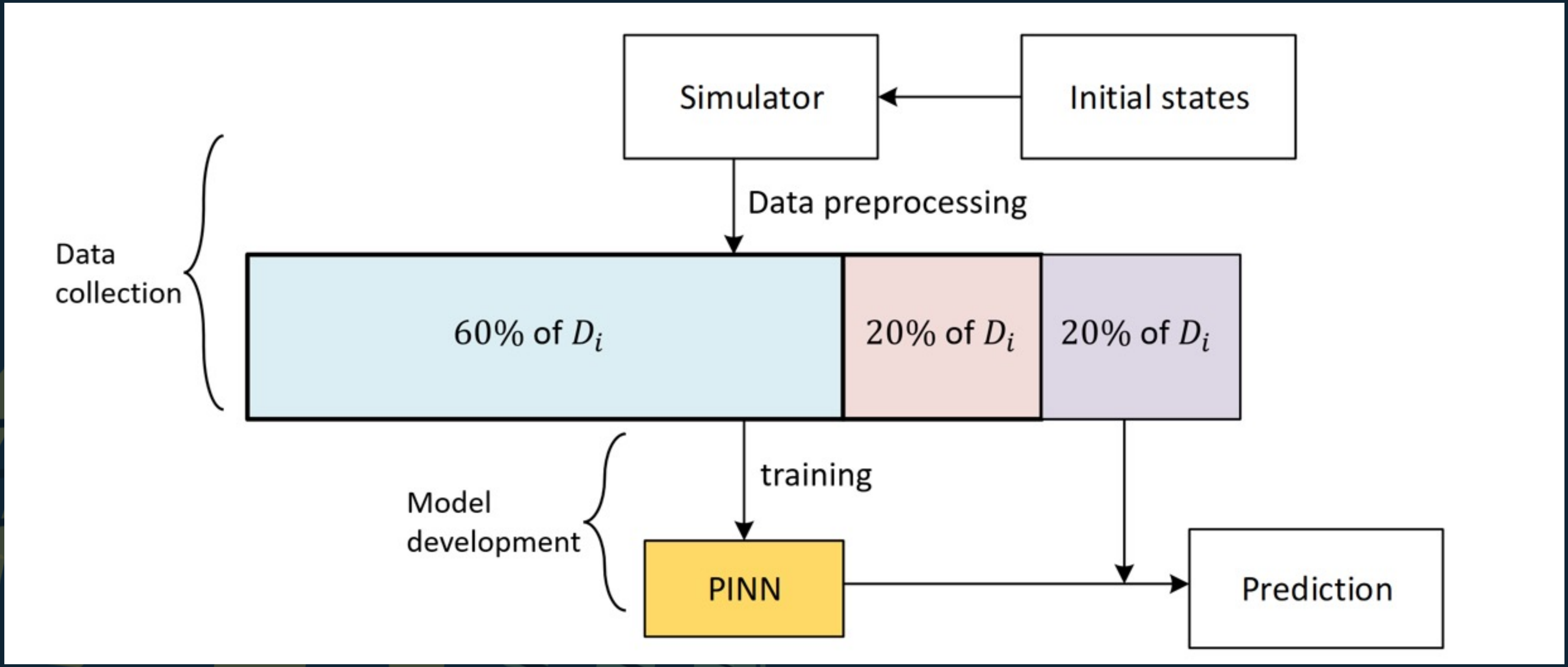
- A neural network with dense layers was used in PINN

$$NN(x) = W_n \ldots \sigma_2(W_2\sigma_1(W_1x + b_1) + b_2) \ldots + b_n$$

- The residual of the simplified physics model was combined within the mismatch in the training data on the state variables

$$L(p) = (NN(0) - x_0)^2 + \sum_k (PINN(t_{k+1}) - x_{k+1})^2$$

- The ADAM algorithm was run first and then the BFGS algorithm was used to precisely search around the minimum area within a small range.


Simulator
Initial states
Data preprocessing
Data collection
60% of D_i
20% of D_i
20% of D_i
training
Model development
PINN
Prediction

Data collection

- Datasets were collected from a gas lifting oil well simulator
- The sampling time for the transient is smaller than the sampling time for the steady state
- Outputs were added with white noise which follows the normal distribution with zero mean.
- There are 200 dataset groups with different initial states. 160 groups of the collected data were used for training and the rest 40 groups were for evaluation and testing.

Data preprocessing

- The range of the training data is around 3000 to 20000, which is difficult for machine learning algorithms to learn from it.
- Besides, features have different magnitudes. The feature with a large magnitude impacts the neural network model more, as the large numerical values dominate during the calculation of the loss function.
- optimization algorithm adopted in this work, ADAM, uses gradient descent

→ **Normalization**

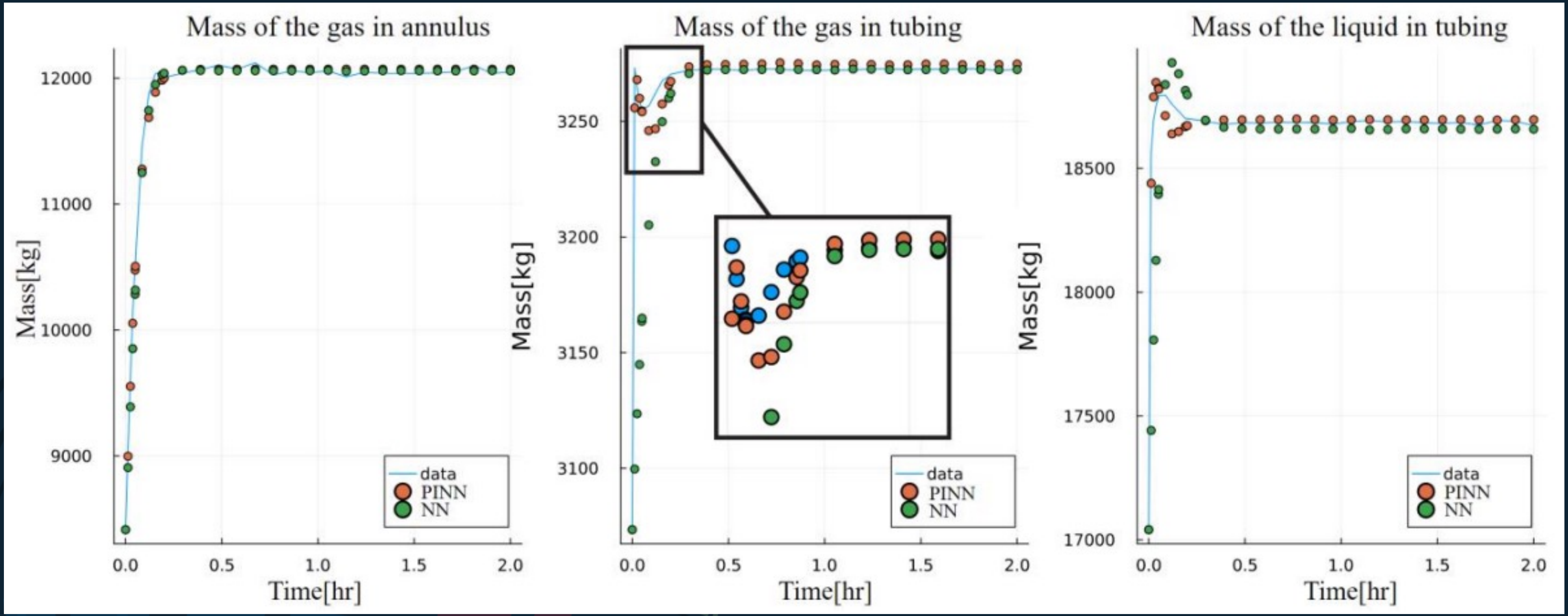
Validation

Tune hyperparameters of the neural network including the number of epochs, the number of layers, the learning rate, the number of nodes in each layer and the activation function for each layer.

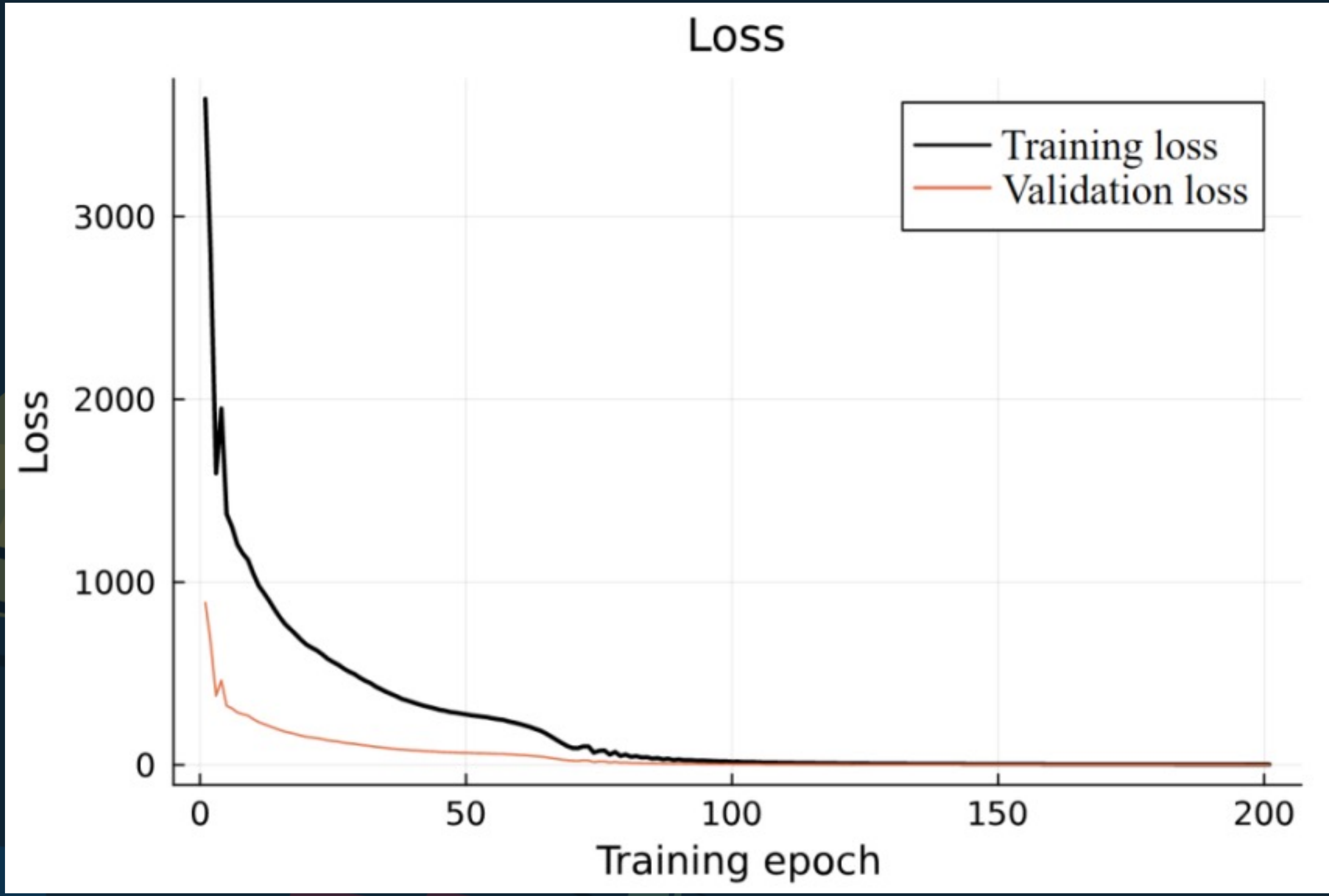
$$S(\theta) = -\frac{1}{m}\sum_{i=1}^{m}(PINN(x_0^i, t) - x^i)^2$$

Result

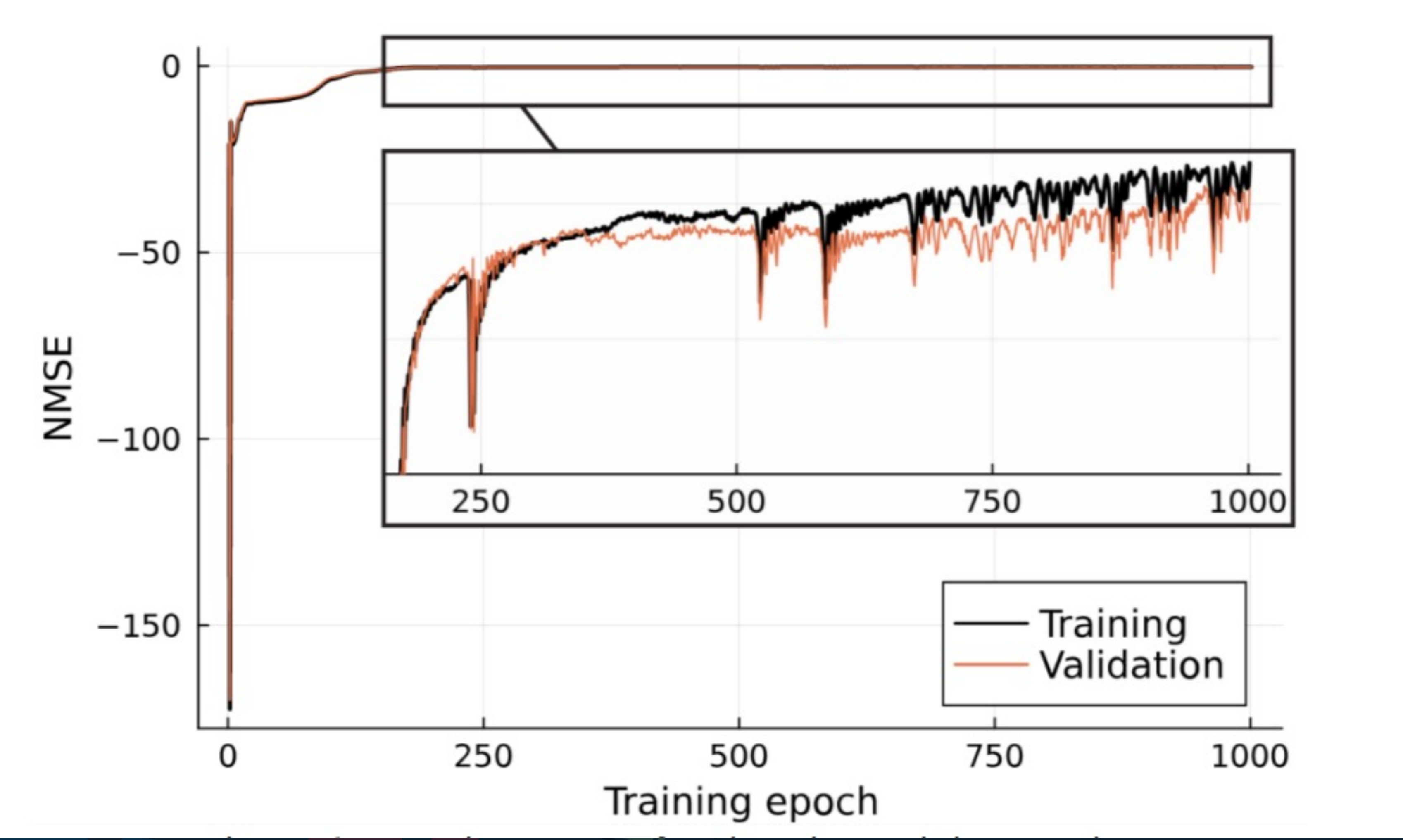
Comparation between PINN and a black box model



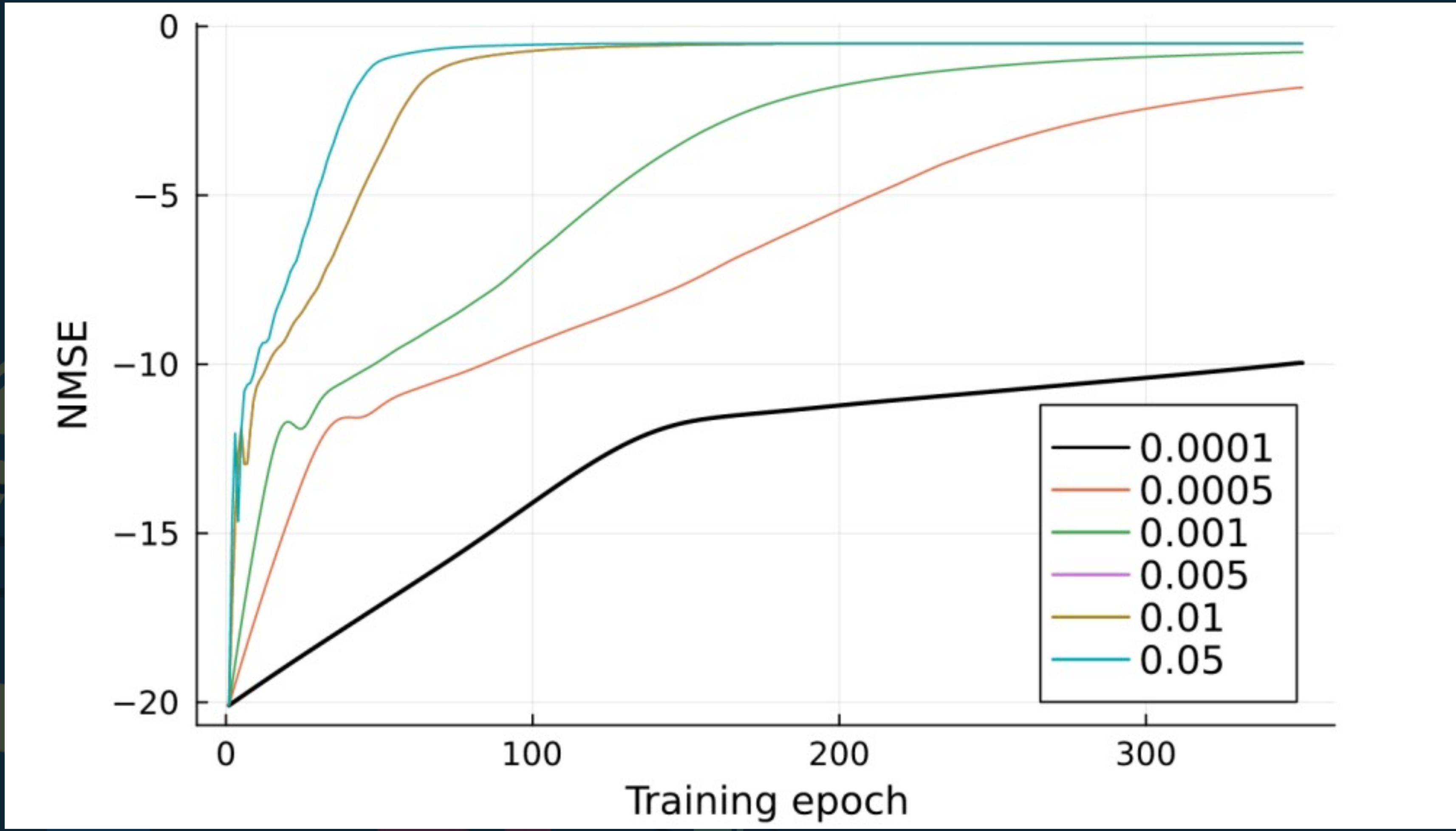
Training loss and validation loss



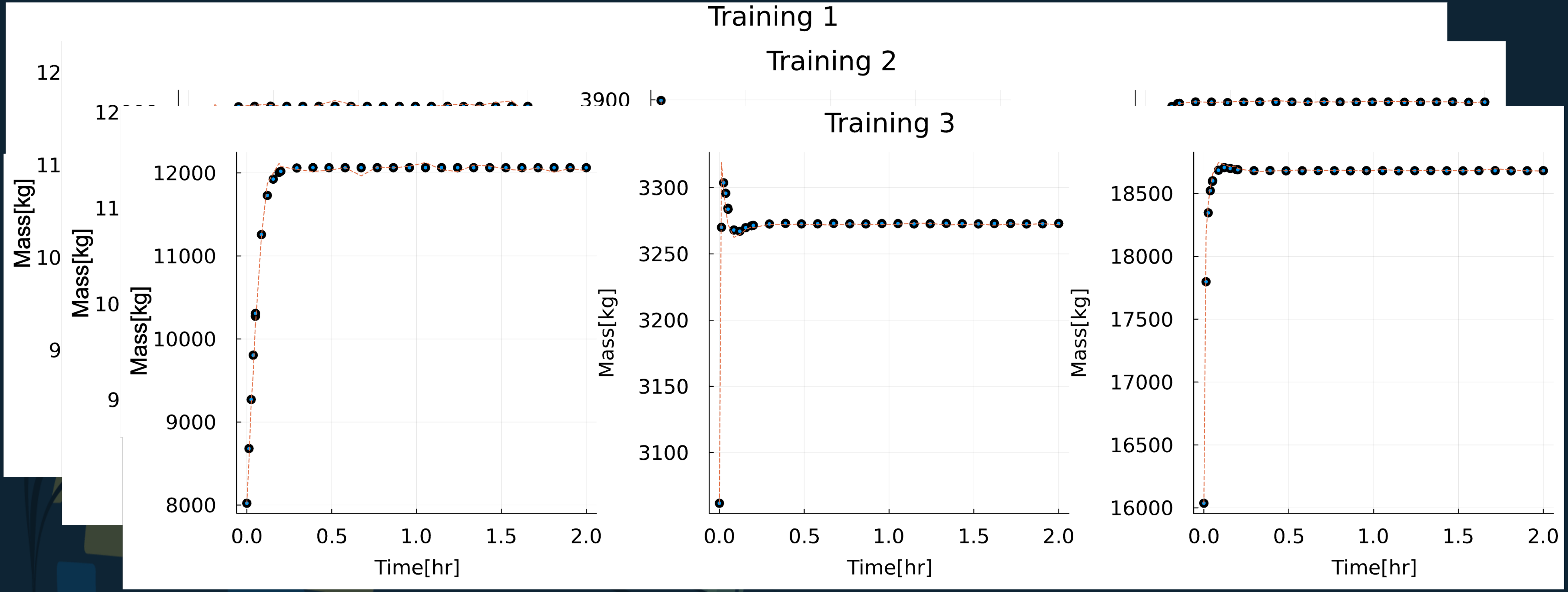
Choose training set size



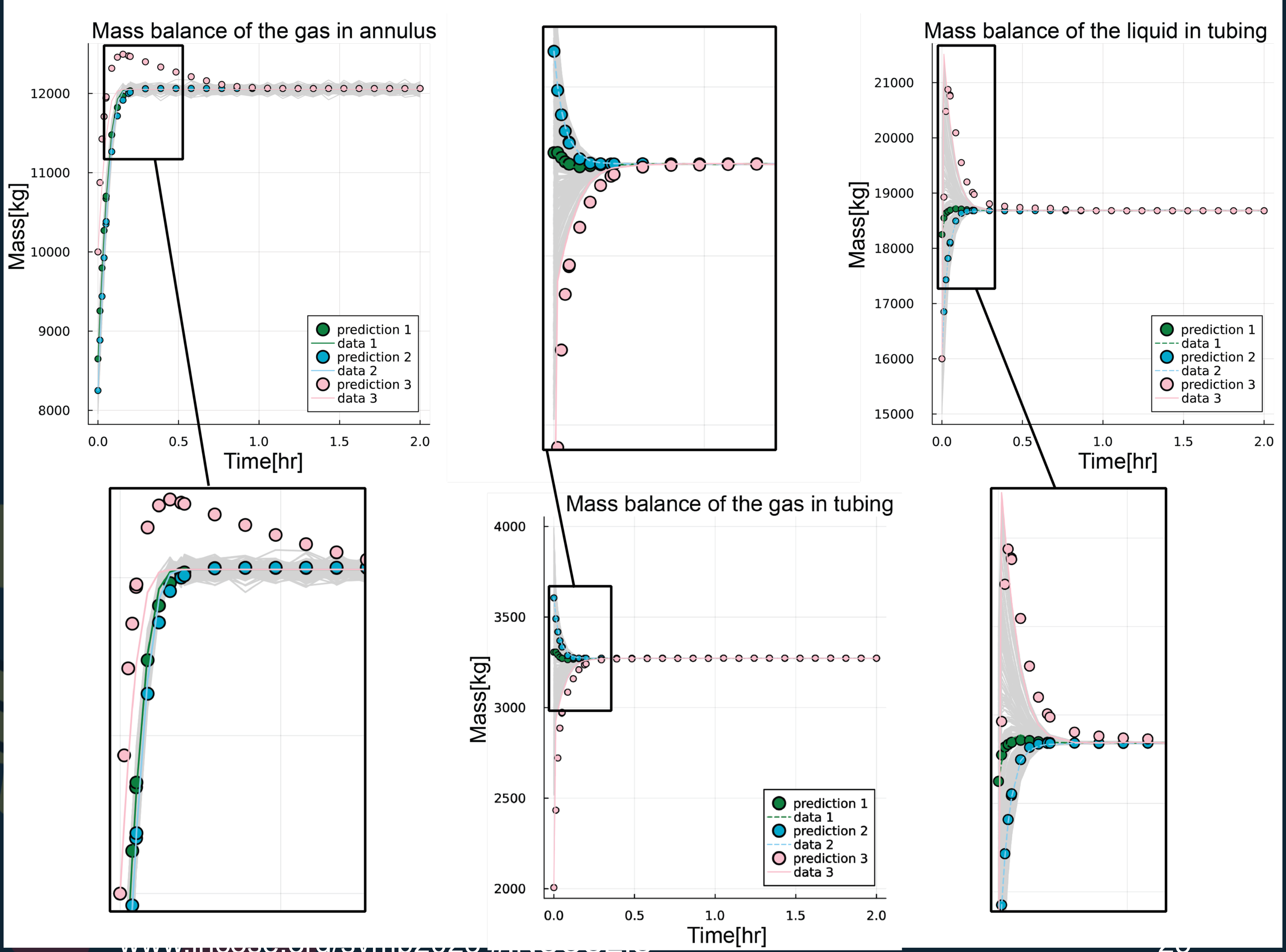
Select learning rate



Training result



Test result



Mass balance of the gas in annulus
Mass[kg]
Time[hr]
prediction 1
data 1
prediction 2
data 2
prediction 3
data 3
Mass balance of the liquid in tubing
Mass[kg]
Time[hr]
Mass balance of the gas in tubing
Mass[kg]
Time[hr]

Discussion & Conclusion

Discussion

- The design of the physics model is subject to certain limitations due to the connection between the simplified physics model and the neural network in PINN.
- The prediction of the performance can only be in the training range. With an untrained initial state, the test performance will have a significant bias from the true output.
- In the validation part, grid search using cross-validation can be an alternative for automatically seeking optimum hyperparameters if the programming environment allows so.

Conclusion

- This research study set out to propose a physics-informed data-driven method for modelling a gas lifting oil well.
- The results of this study show that the trained PINN model is able to predict the outputs of states with initial states which is within the training range for both steady-state and transient.
- The potential application of the PINN model is an auxiliary model based on data and prior physical knowledge of the oil production process, which might help provide information for model-based control.

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