Data-Driven Hierarchical Neural Network Modeling for High-Pressure Feedwater Heater Group

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Contents

Introduction

- Data-driven machine learning applications
  - Image identification
  - Speech recognition
  - Natural Language Understanding
  - …
- Machine learning in thermal power industry
  - High-pressure feedwater heater group modeling

Introduction

- High-Pressure Feedwater Heater Group (HPFHG)[2]
  - Consists of three high-pressure feed-water heaters(HPFHs)
    - Cascade structure
  - HPFHG Modeling requirements
    - Modeling the heater group as a whole √
    - Modeling each single heater at the same time √

Introduction

- HPFHG Modeling Techniques
  - Physical modeling techniques
    - Based on the first law of heat transfer, the second law of heat transfer, the law of conservation of mass and Newtonian cooling equation
  - Flaws:
    - Some coefficients are dynamically changing [12,9].
    - Some coefficients have no sensor to measure [1].

Introduction

- HPFHG Modeling Techniques
  - Data driven methods
    - Traditional ‘black box’ artificial neural network (ANN) model
  - Flaws:
    - Modeling the heater group as a whole √
    - Modeling each single heater at the same time ×

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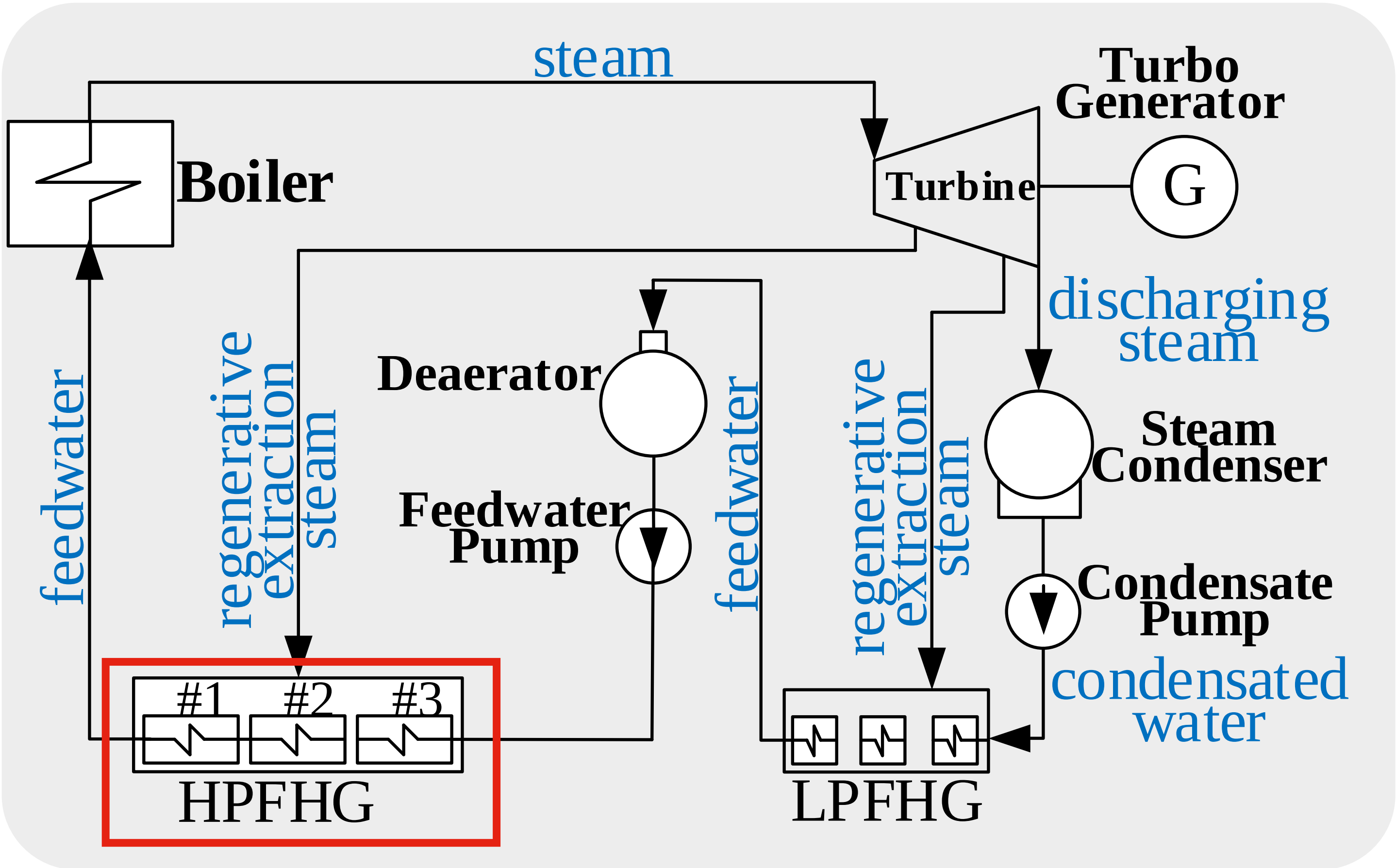
Introduction

- Our method
  - Data-Driven Hierarchical Neural Network Modeling Approach
    - Inspired by the physical cascade structure of the heater group
    - Modeling the heater group as a whole √
    - Modeling each single heater at the same time √

Contents

Industrial Background

- Thermal Power Plant Regenerative System
  - Improve thermal efficiency
  - Save fuel
  - Reduce pollution



Industrial Background

- HPFHG modelling objective
  - Find out the relationship between the feedwater outlet temperature and other variables
- HPFHG modelling significance: [4,5,7]
  - Find out the best working condition
  - Fault detection
  - Improve efficiency
  - Reduce emissions

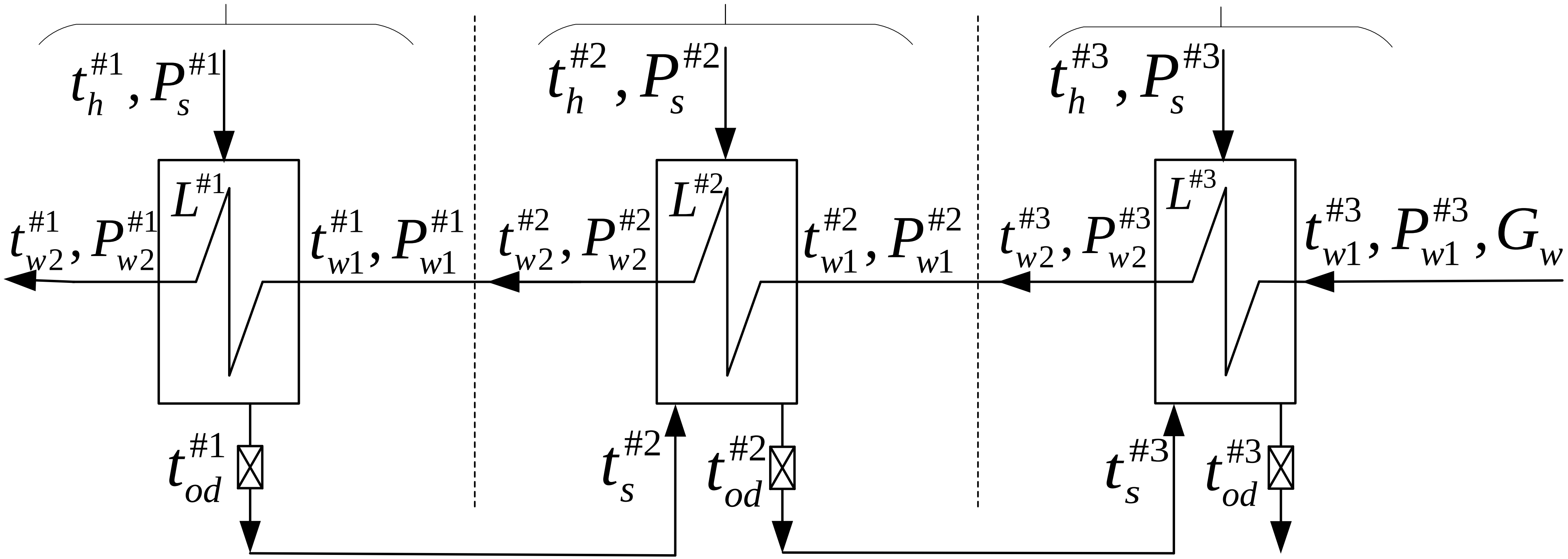
Industrial Background

- Variables for a single High-Pressure Feedwater Heater Modeling
  - Relative
  - Available

t_{w2} (°C) — the feedwater outlet temperature of an HPFH
t_{w1} (°C) — the feedwater inlet temperature of an HPFH
t_h (°C) — the inlet steam temperature of an HPFH
P_s (MPa) — the inlet steam pressure of an HPFH
L (mm) — the water level in an HPFH
P_{w1} (MPa) — the feedwater inlet pressure of an HPFH
P_{w2} (MPa) — the feedwater outlet pressure of an HPFH
G_w (t/s) — the feedwater flow throughout an HPFHG
t_{od} (°C) — the drain temperature of an HPFH
t_s (°C) — the superior drain temperature of an HPFH

Industrial Background

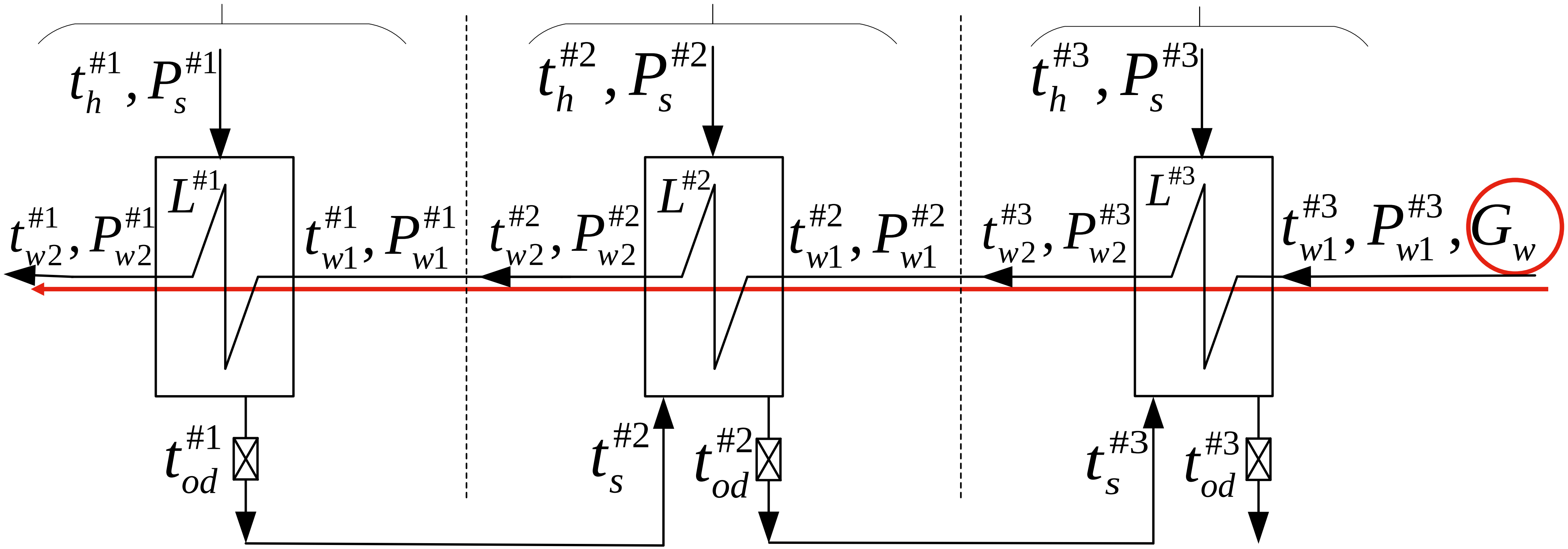
- High-Pressure Feedwater Heater Group



Industrial Background

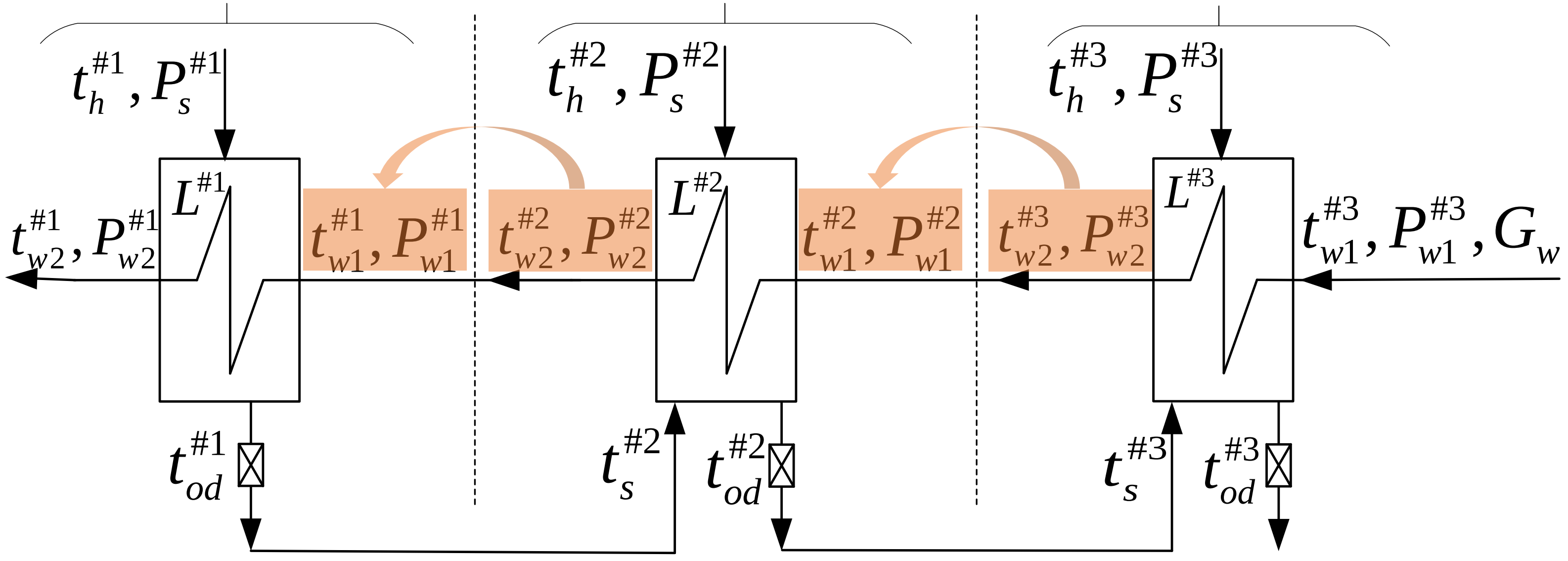
- High-Pressure Feedwater Heater Group

A Shared Variable



Industrial Background

- High-Pressure Feedwater Heater Group



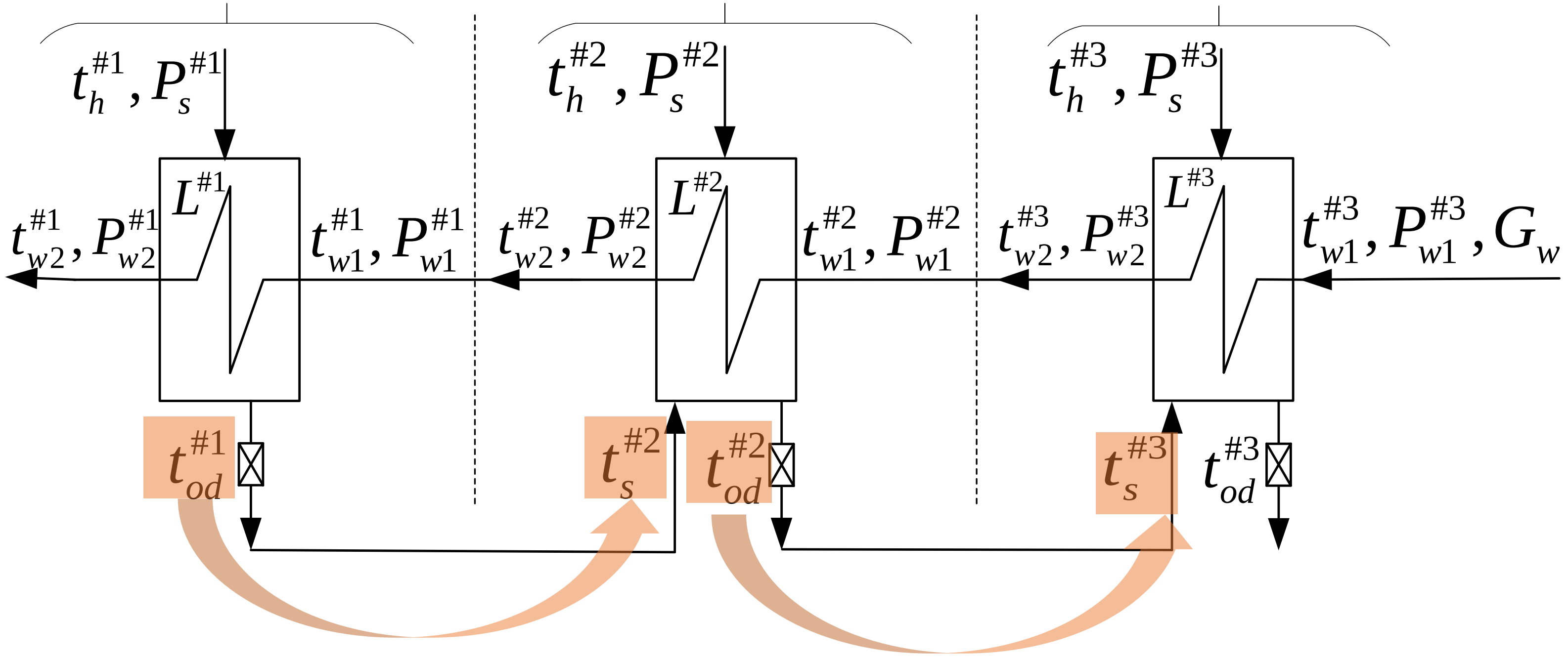
Cascade variable pairs

$$t_{w1}^{\#2}=t_{w2}^{\#3},\ P_{w1}^{\#2}=P_{w2}^{\#3}$$

$$t_{w1}^{\#1}=t_{w2}^{\#2},\ P_{w1}^{\#1}=P_{w2}^{\#2}$$

Industrial Background

- High-Pressure Feedwater Heater Group



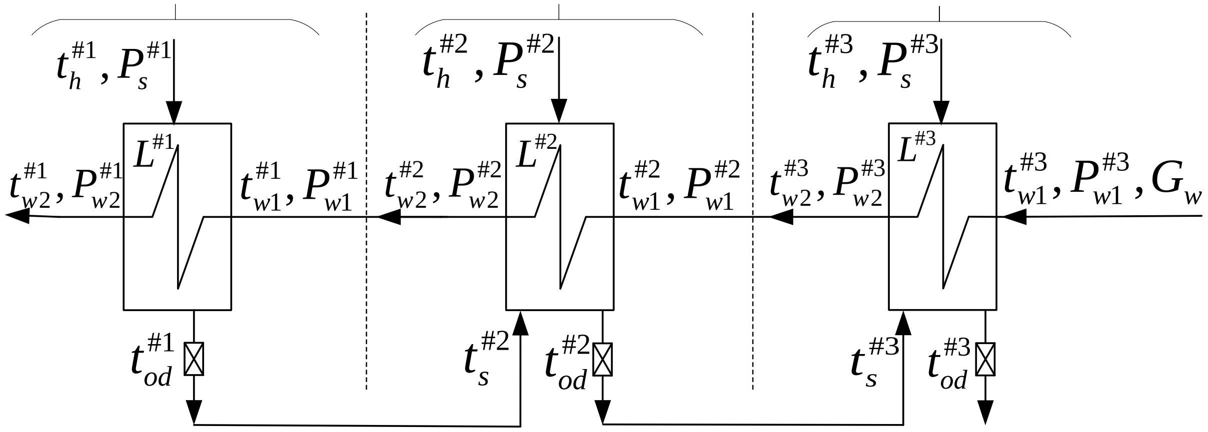
Cascade variable pairs

$$t_{od}^{\#2} = t_s^{\#3}$$

$$t_{od}^{\#1} = t_s^{\#2}$$

Industrial Background

- Variables for Single Heater #3 / #2 / #1 Modeling



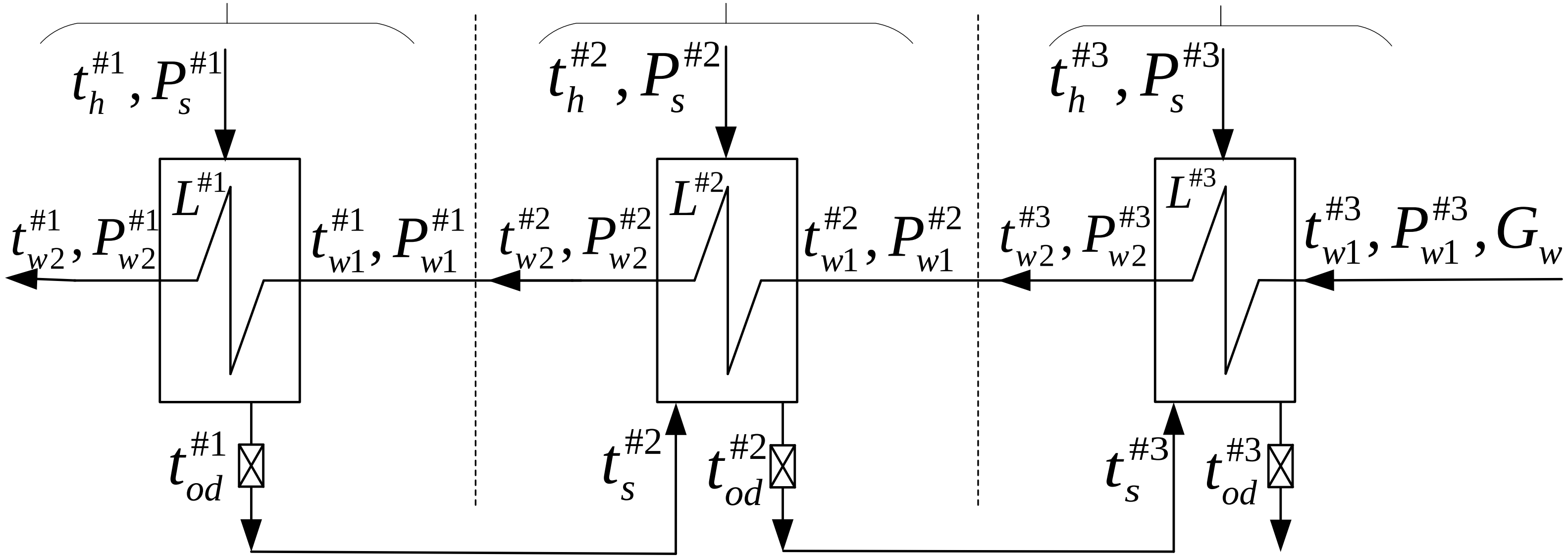
$$x^{\#3}=[G_w,t_{w1}^{\#3},t_h^{\#3},P_s^{\#3},L^{\#3},P_{w1}^{\#3},P_{w2}^{\#3},t_{od}^{\#3},\ t_s^{\#3}],\ y^{\#3}=t_{w2}^{\#3}.$$

$$x^{\#2}=[G_w,t_{w1}^{\#2},t_h^{\#2},P_s^{\#2},L^{\#2},P_{w1}^{\#2},P_{w2}^{\#2},t_{od}^{\#2},\ t_s^{\#2}],\ y^{\#2}=t_{w2}^{\#2}.$$

$$x^{\#1}=[G_w,t_{w1}^{\#1},t_h^{\#1},P_s^{\#1},\ L^{\#1},\ P_{w1}^{\#1},P_{w2}^{\#1},t_{od}^{\#1}],\qquad y^{\#1}=t_{w2}^{\#1}.$$

Industrial Background

- Variables for HPFHG Modeling

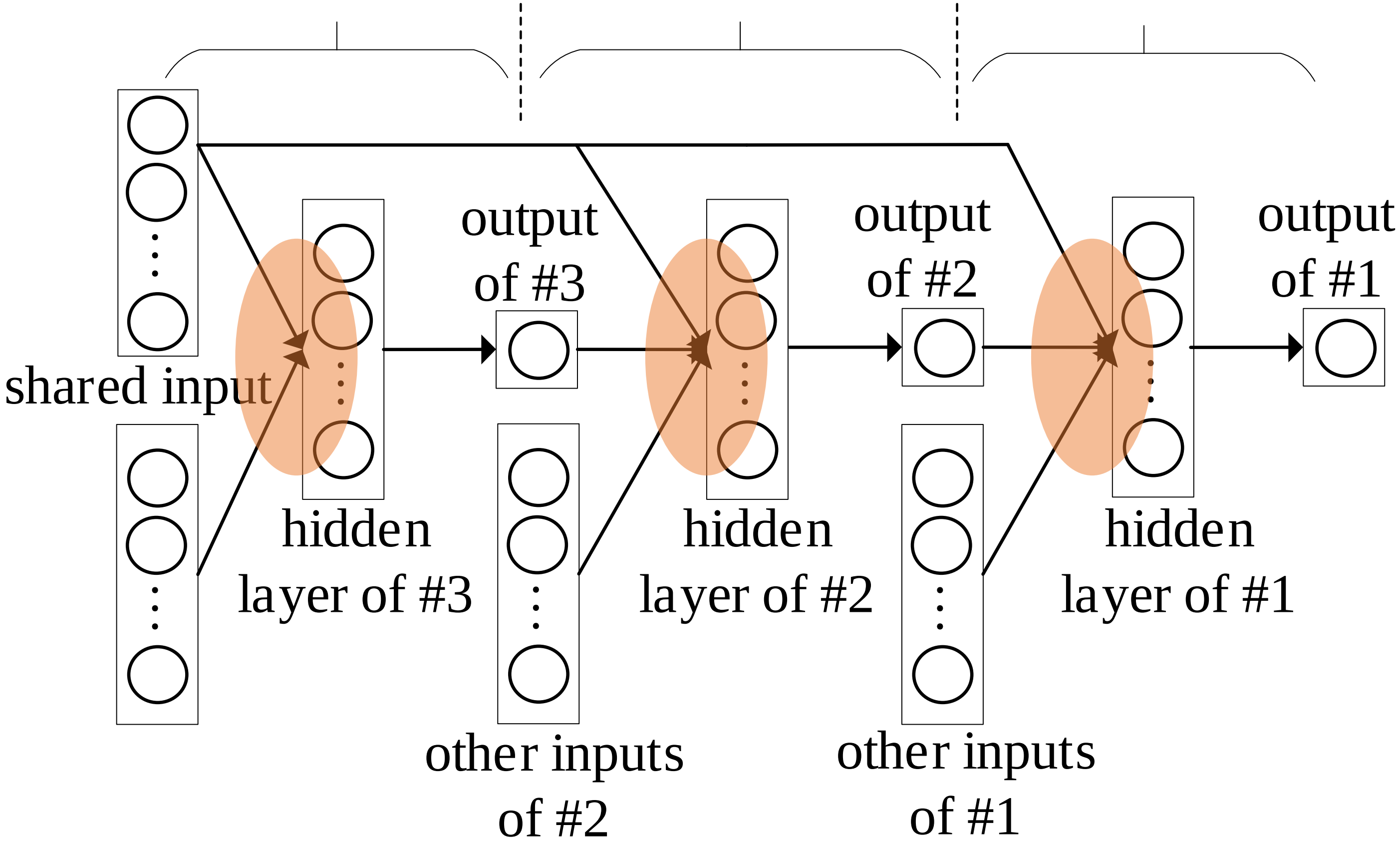


$$X = x^{\#3} \cup x^{\#2} \cup x^{\#1},\ y = t_{w2}^{\#1}$$

Contents

Data-Driven Hierarchical Neural Network Modeling

- Architecture
  - Consists of 3 subnets
    - net #3 → HPFH #3
    - net #2 → HPFH #2
    - net #1 → HPFH #1



Data-Driven Hierarchical Neural Network Modeling

- Loss function: multi-task learning

$$L = \sum_{j=1}^{N} \left(\frac{1}{m} W_j \sum_{i=1}^{m} \left(y_j^{(i)} - \hat{y}_j^{(i)} \right)^2 \right)$$

N is the number of subnets
W_j is the weight of subnet j
m is the number of training samples
$y_j^{(i)}$ is the true output of the i-th sample of subnet j
$\hat{y}_j^{(i)}$ is the predicted output of subnet j

- Jointly training net #3, #2 and #1
  - Modeling the heater group as a whole √
  - Modeling each single heater at the same time √

Contents

Experiments and Results

❑ Experimental Data

- collected from a thermal power unit whose capacity is 1000MW
- collected over a month without interruption
- sampling interval is 5 minutes
- m=10081

Experiments and Results

❑ Performance Evaluation Criteria

$$\mathrm{MAE} = \frac{1}{\mathrm{m}}\sum_{\mathrm{i}=1}^{\mathrm{m}} |y^{(i)} - \hat{\mathrm{y}}^{(i)}|, \qquad \mathrm{MAPE} = \left(\frac{1}{\mathrm{m}}\sum_{\mathrm{i}=1}^{\mathrm{m}} \left|\frac{y^{(i)} - \hat{\mathrm{y}}^{(i)}}{y^{(i)}}\right|\right) \times 100\%,$$

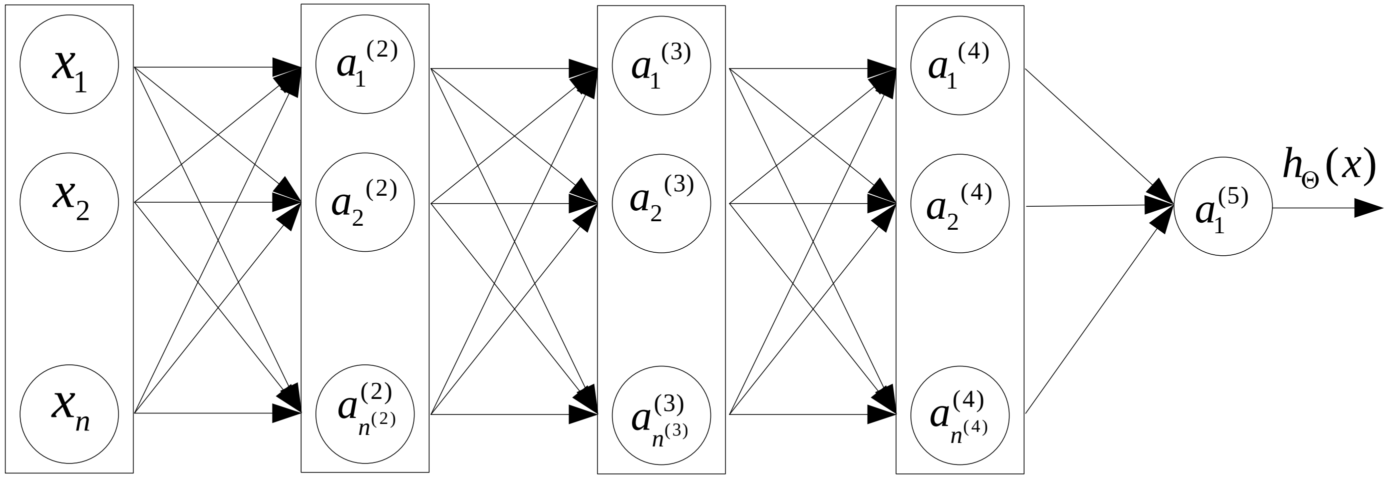
$$\mathrm{RMSE} = \sqrt[2]{\frac{1}{\mathrm{m}}\sum_{\mathrm{i}=1}^{\mathrm{m}} (y^{(i)} - \hat{\mathrm{y}}^{(i)})^2}, \qquad \mathrm{RMSPE} = \left(\sqrt[2]{\frac{1}{\mathrm{m}}\sum_{\mathrm{i}=1}^{\mathrm{m}} \left(\frac{y^{(i)} - \hat{\mathrm{y}}^{(i)}}{y^{(i)}}\right)^2}\right) \times 100\%.$$

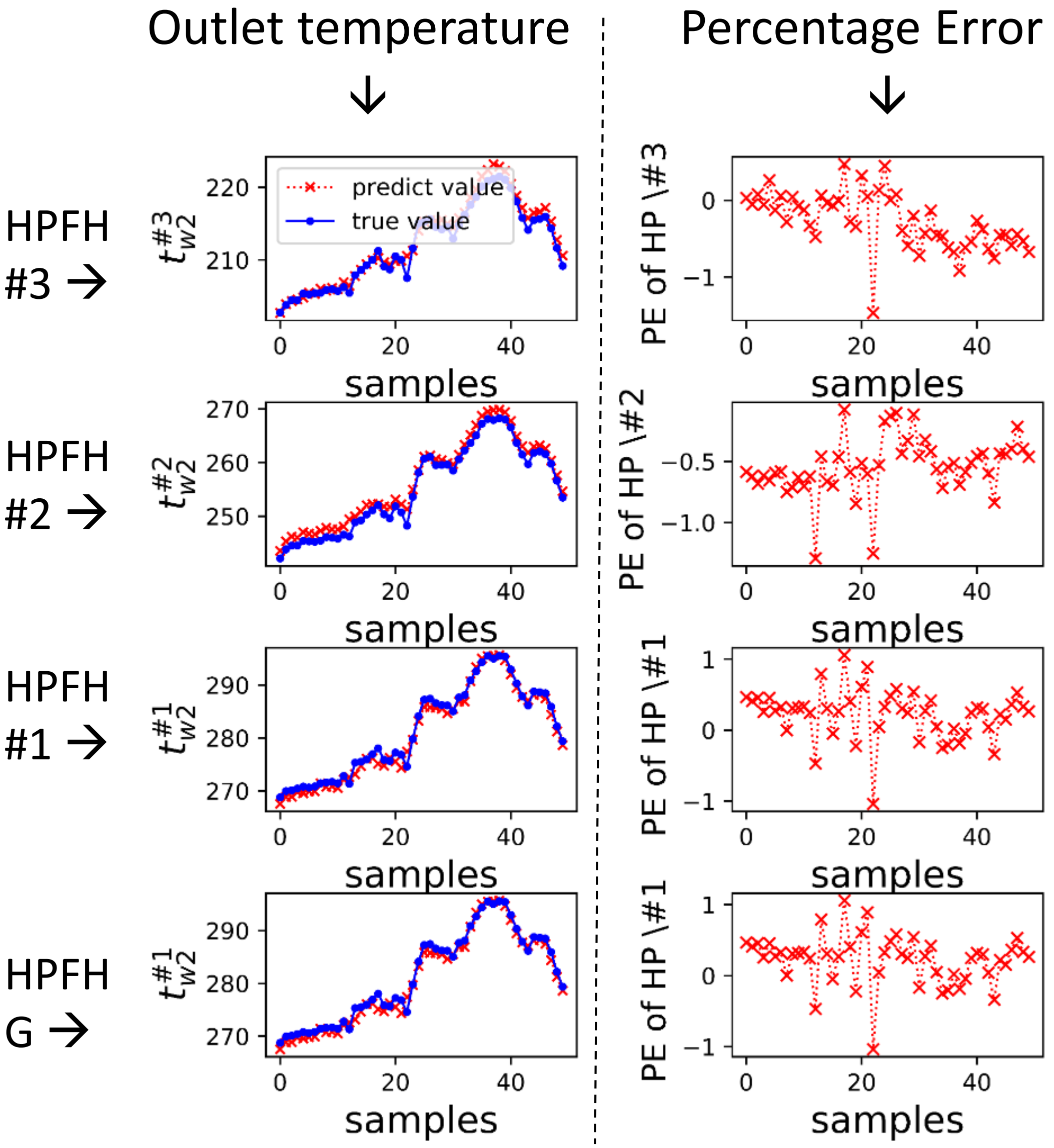
Experiments and Results

- Experimental Setting
  - $\text{training set} : \text{test set} = 70\% : 30\%$
  - $W_3 : W_2 : W_1 = 1 : 1 : 1$
  - Overfitting strategy: early stop

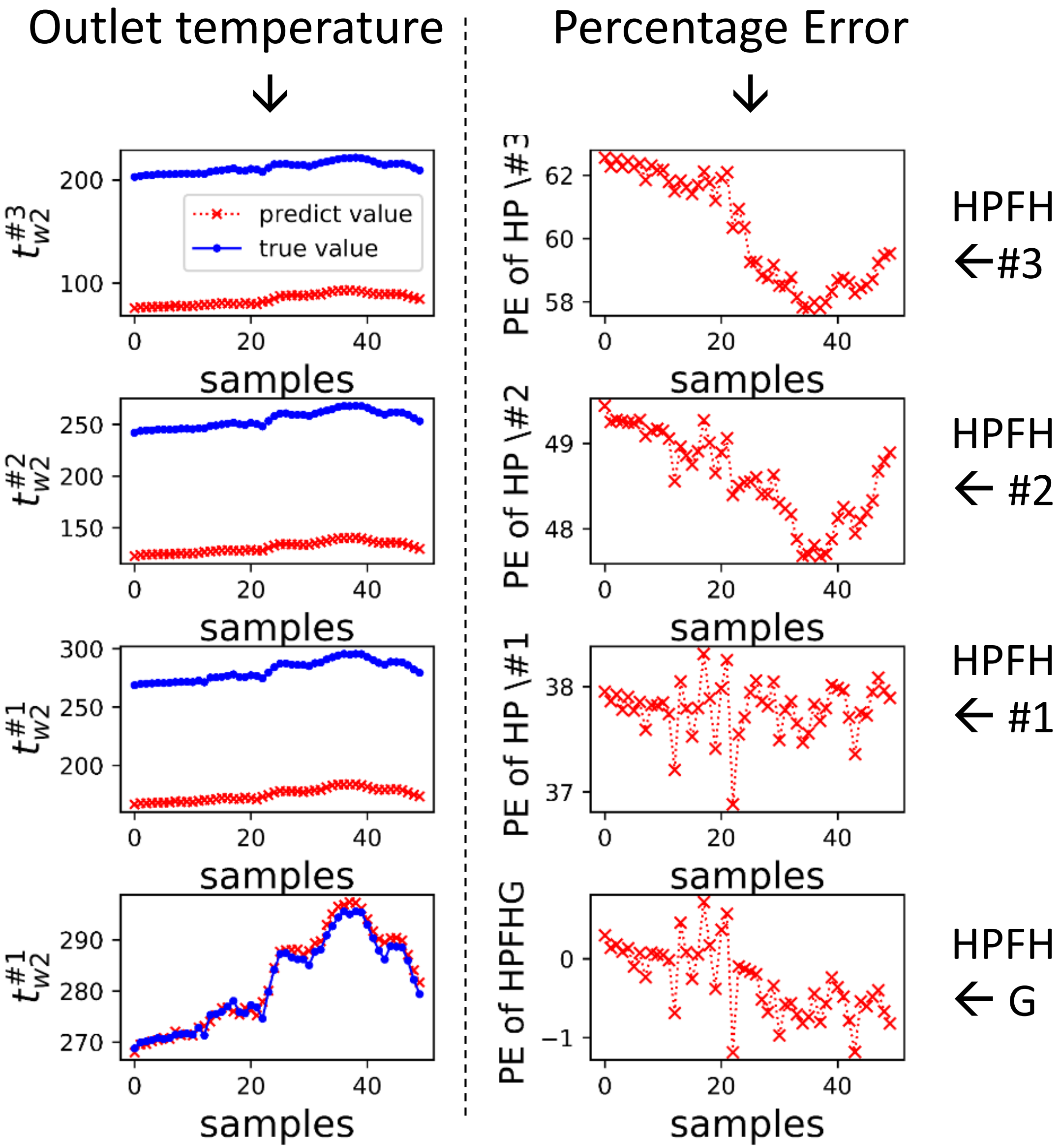
Experiments and Results

- Contrast experiment
  - A “black box” ANN model with three hidden layers





The proposed method



The ‘black box’ ANN

Experiments and Results

- results comparison

Table 1. Performance comparison

Methods	the proposed method				the 'black-box' method			
Criteria	MAE (°C)	RMSE (°C)	MAPE (%)	RMSPE (%)	MAE (°C)	RMSE (°C)	MAPE (%)	RMSPE (%)
HPFH#3	0.936	1.073	0.458	0.525	125.14	125.17	61.19	61.22
HPFH#2	1.764	1.980	0.731	0.832	120.70	120.78	49.03	49.03
HPFH#1	0.691	0.894	0.253	0.326	102.89	103.01	37.75	37.75
HPFHG	0.691	0.894	0.253	0.326	1.1254	1.3643	0.409	0.494

Contents

Conclusions

❑ Contributions

- ❖ Defined an industrial application problem
- ❖ Provided a data-driven hierarchical neural network modeling approach to model HPFHG and each single HPFH at the same time
- ❖ The proposed model can be used to find out the best operating condition, detect system faults, save fuel and reduce pollution.

Thank you