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Cost optimal predictive demand response control

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- Master in mechanical engineering
- Master in control

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Demad Respose (DR)

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Why DR

- Smart buildings
- End user energy cost saving
- Energy supplier load management

Predictive demand response control (Optimal)

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Optimal control (scheduling)

- Scheduling when we should buy energy
- Scheduling when we should store ad how much
- **Target is minimizing the energy cost**

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Challenges

- Cost optimal control
- Practical procedure
- Error in prediction

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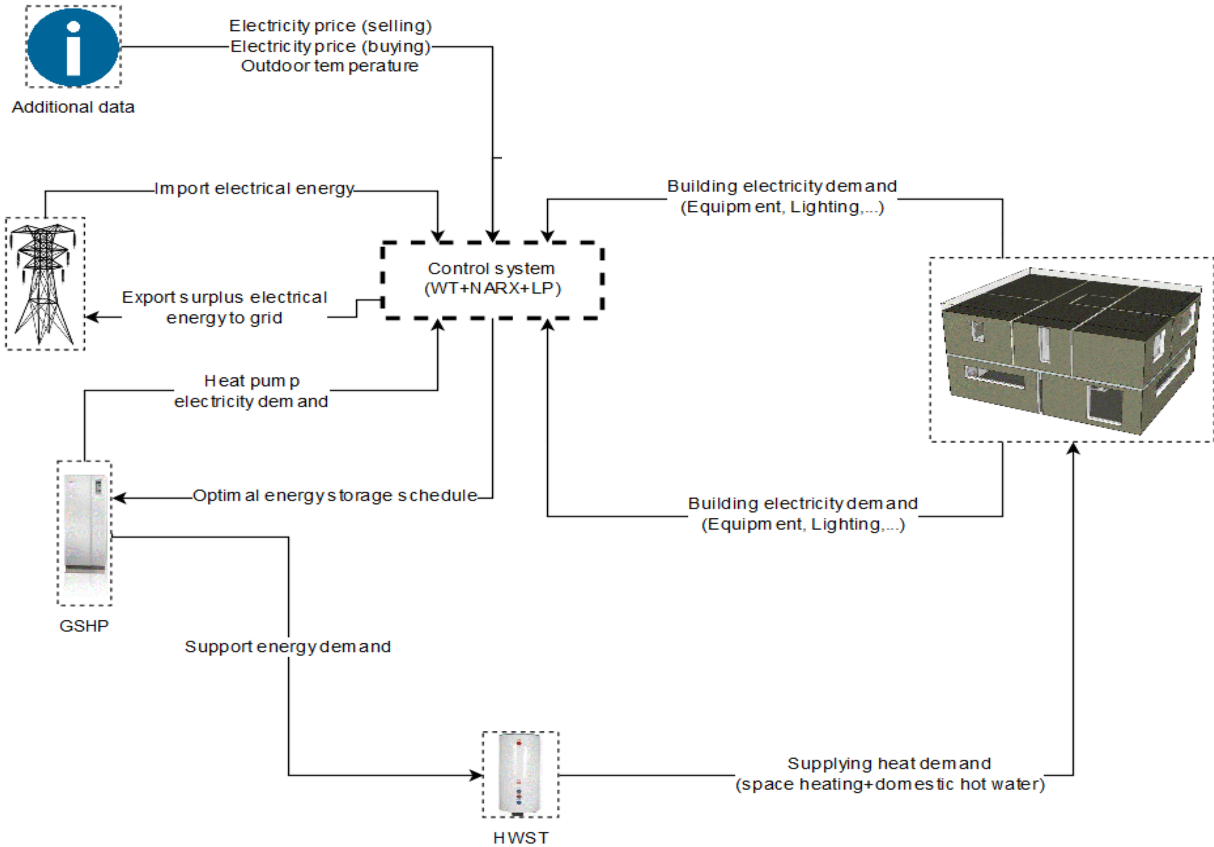
Main steps

- Data analysis
- Predictor model
- Optimizer (DR control)



Additional data
Electricity price (selling)
Electricity price (buying)
Outdoor temperature
Import electrical energy
Building electricity demand
(Equipment, Lighting,...)
Control system
(WT+NARX+LP)
Export surplus electrical
energy to grid
Heat pump
electricity demand
Optimal energy storage schedule
Building electricity demand
(Equipment, Lighting,...)
GSHP
Support energy demand
Supplying heat demand
(space heating+domestic hot water)
HWST

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Assumption

- Next 24 hours price
- History of heat demand

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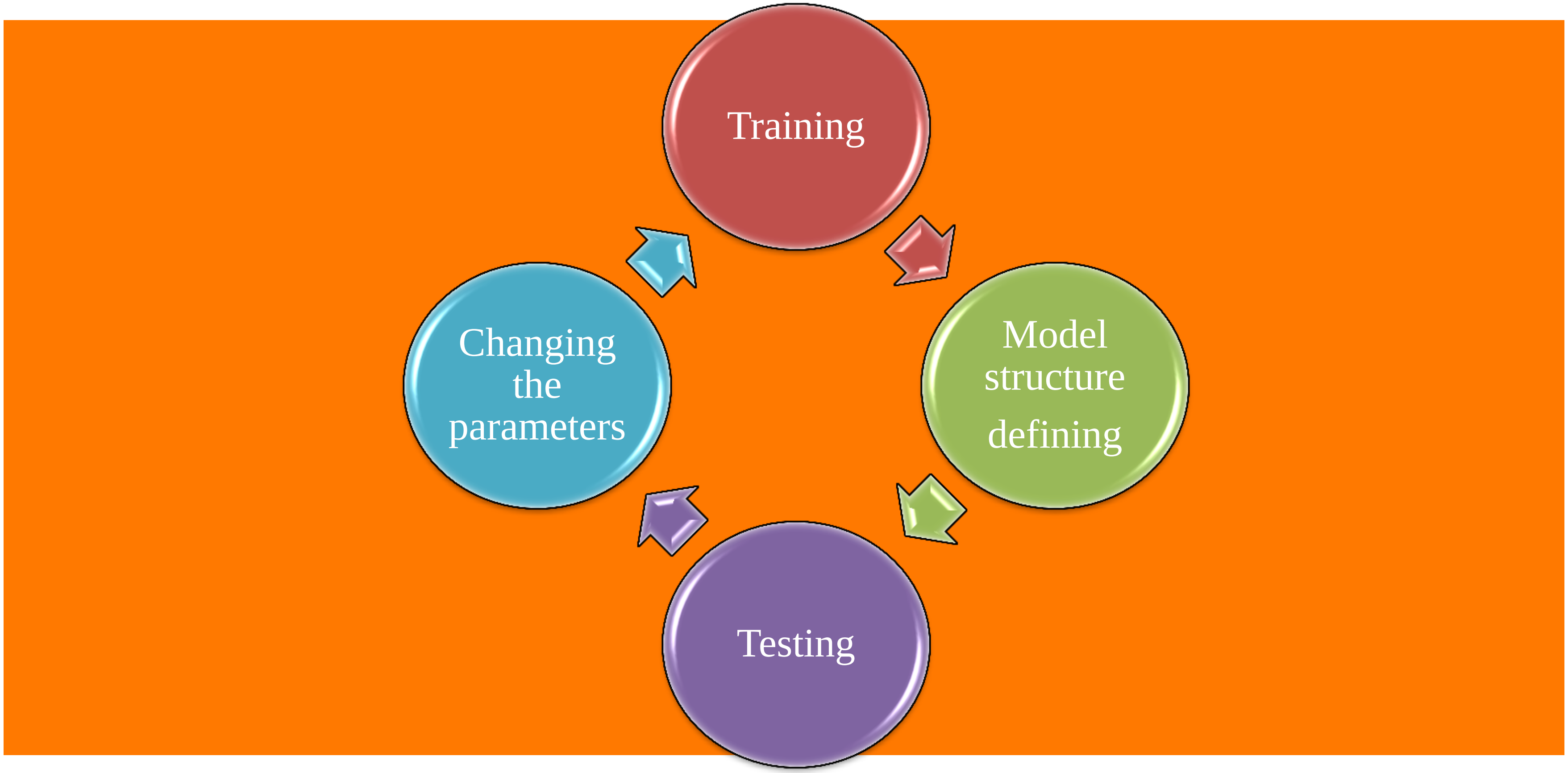
Predictor model

Artificial Neural Network (ANN)


Training
Model structure defining
Testing
Changing the parameters

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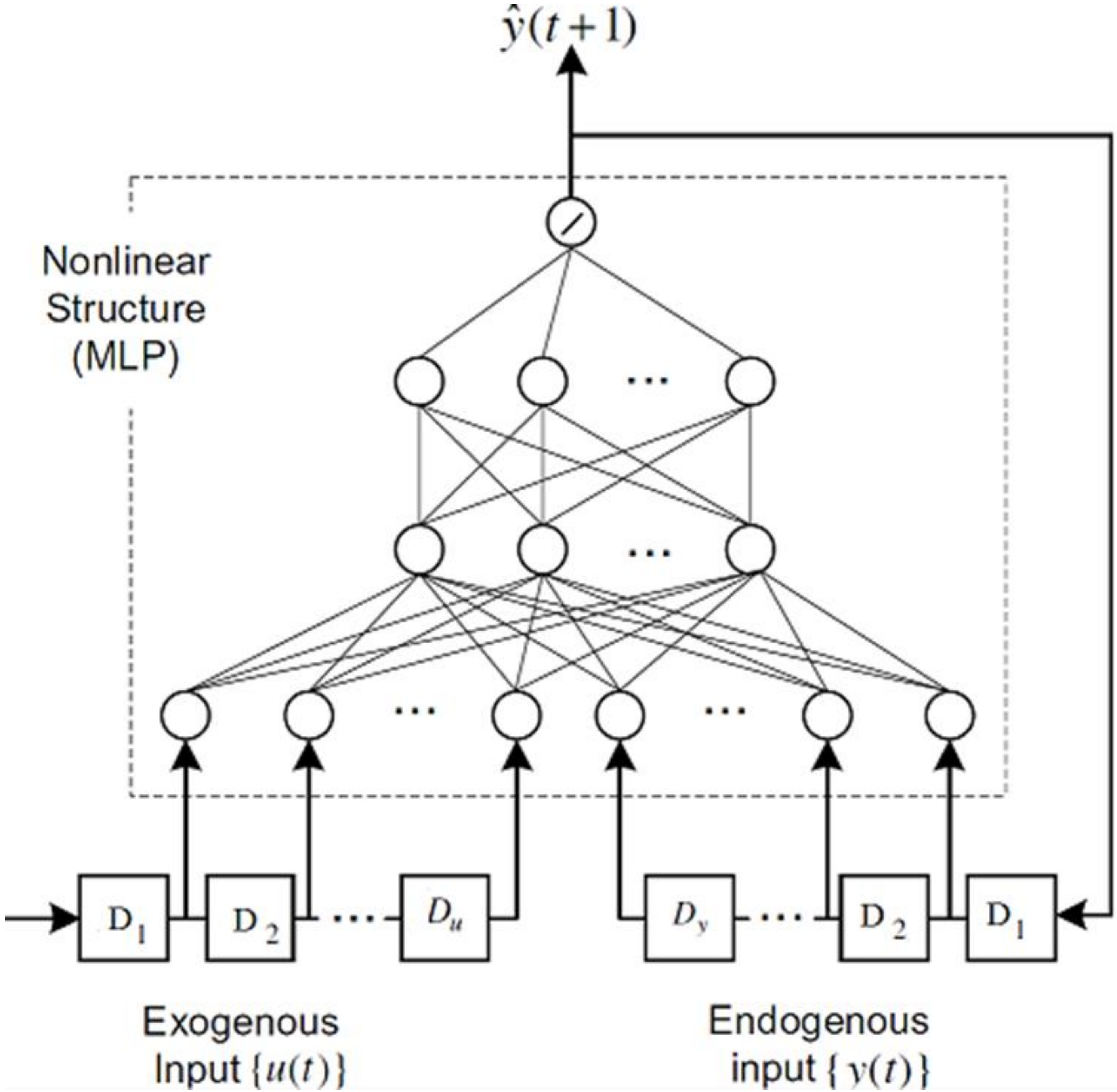
Model parameters

- Layers
- Neuron numbers



$\hat{y}(t+1)$
Nonlinear Structure (MLP)
D_1
D_2
D_u
D_y
D_2
D_1
Exogenous Input $\{u(t)\}$
Endogenous input $\{y(t)\}$

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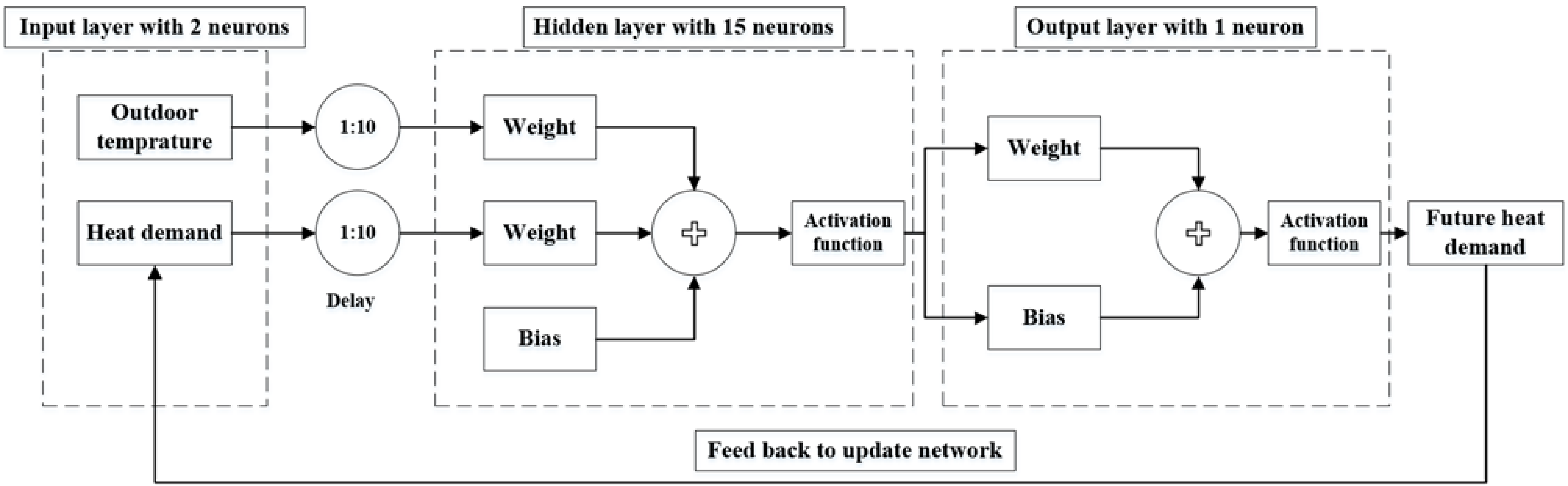
Matlab Toolbox



Input layer with 2 neurons
Hidden layer with 15 neurons
Output layer with 1 neuron
Outdoor temprature
Heat demand
1:10
1:10
Delay
Weight
Weight
Bias
Activation function
Weight
Bias
Activation function
Future heat demand
Feed back to update network

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Training data set

Testing data set

Target data set

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IDA-ICE

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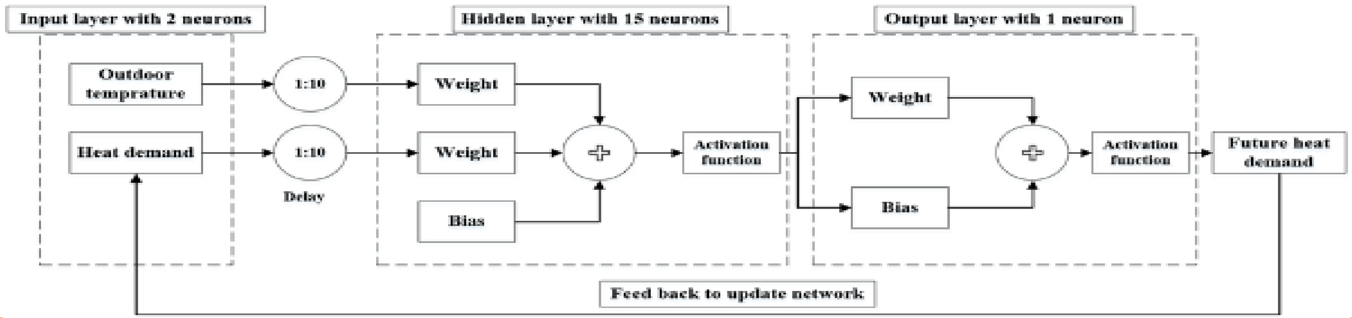

Predictor model configuration

Training data → NARX Model

Training data → Preprocessing (Wavelet) → NARX Model

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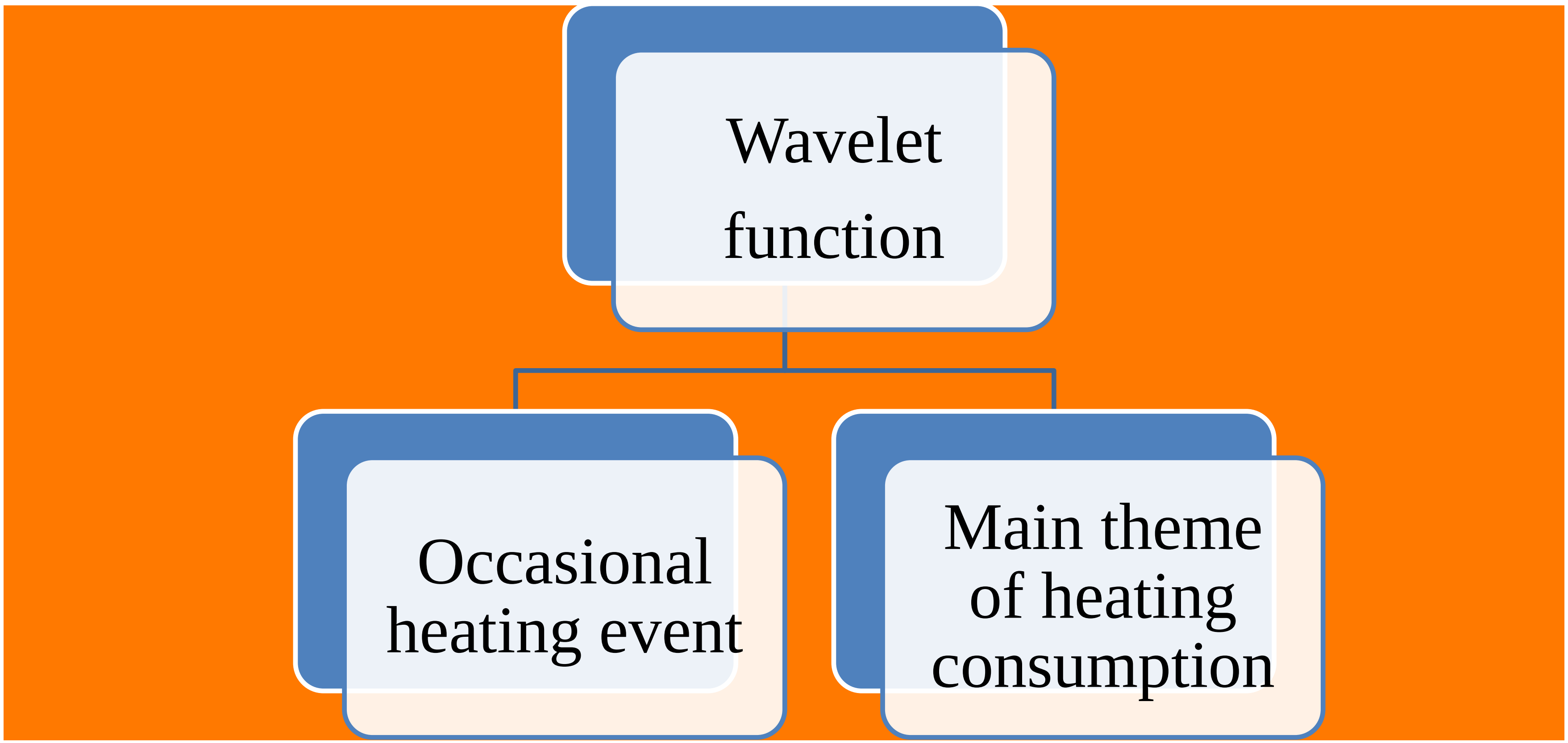

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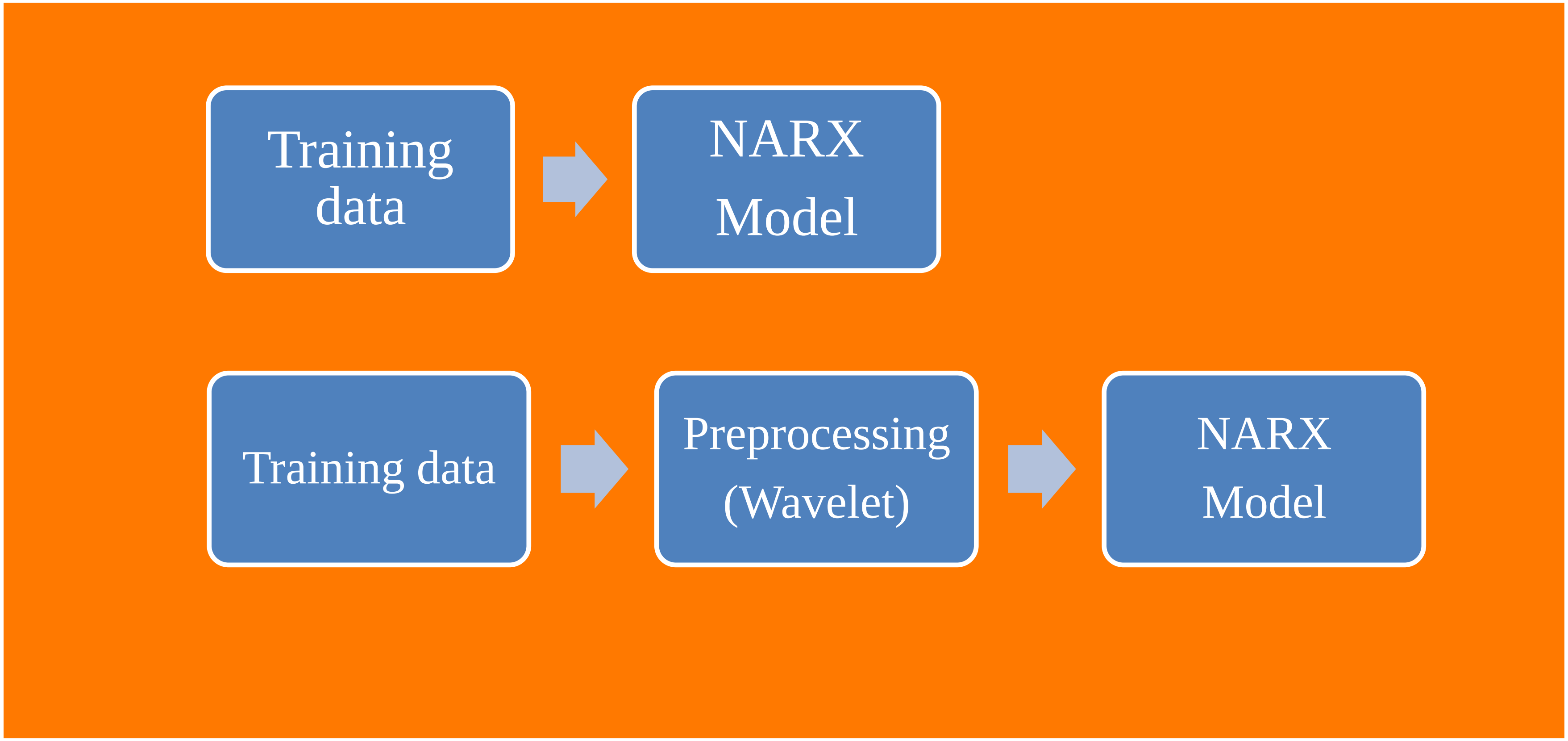

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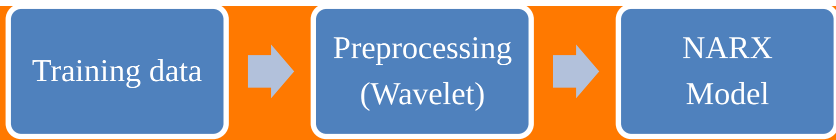
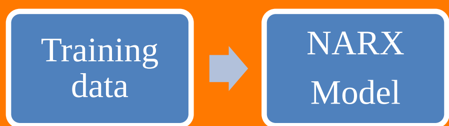
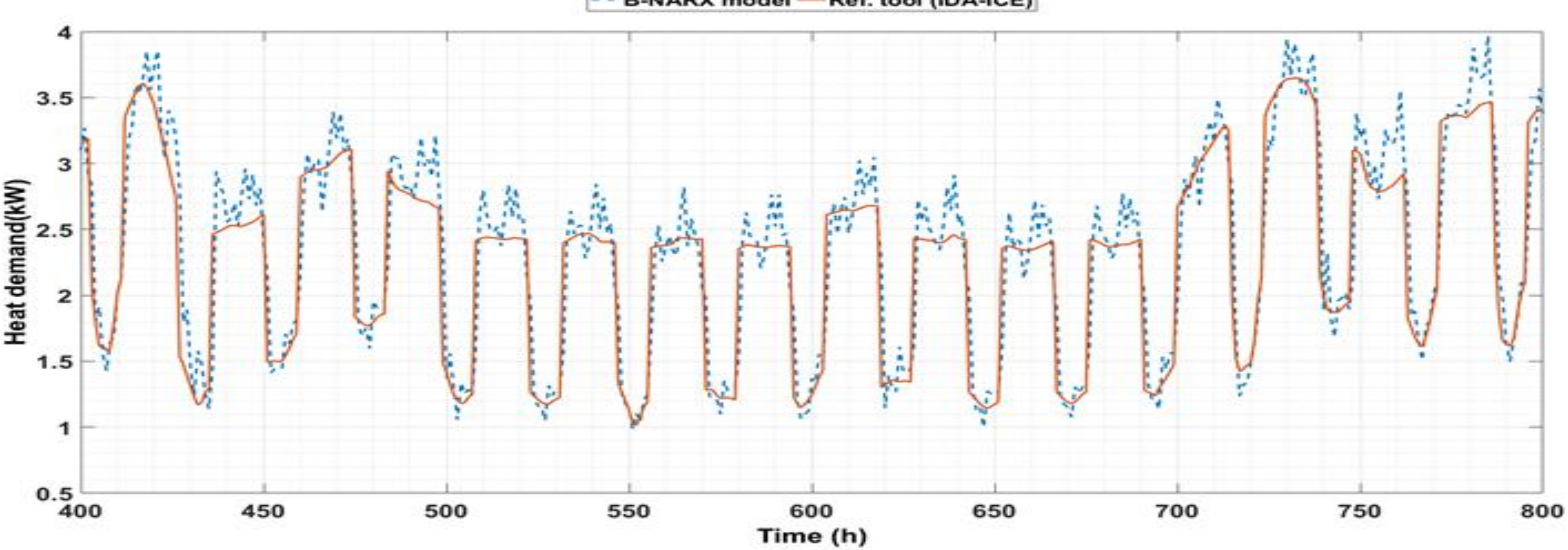
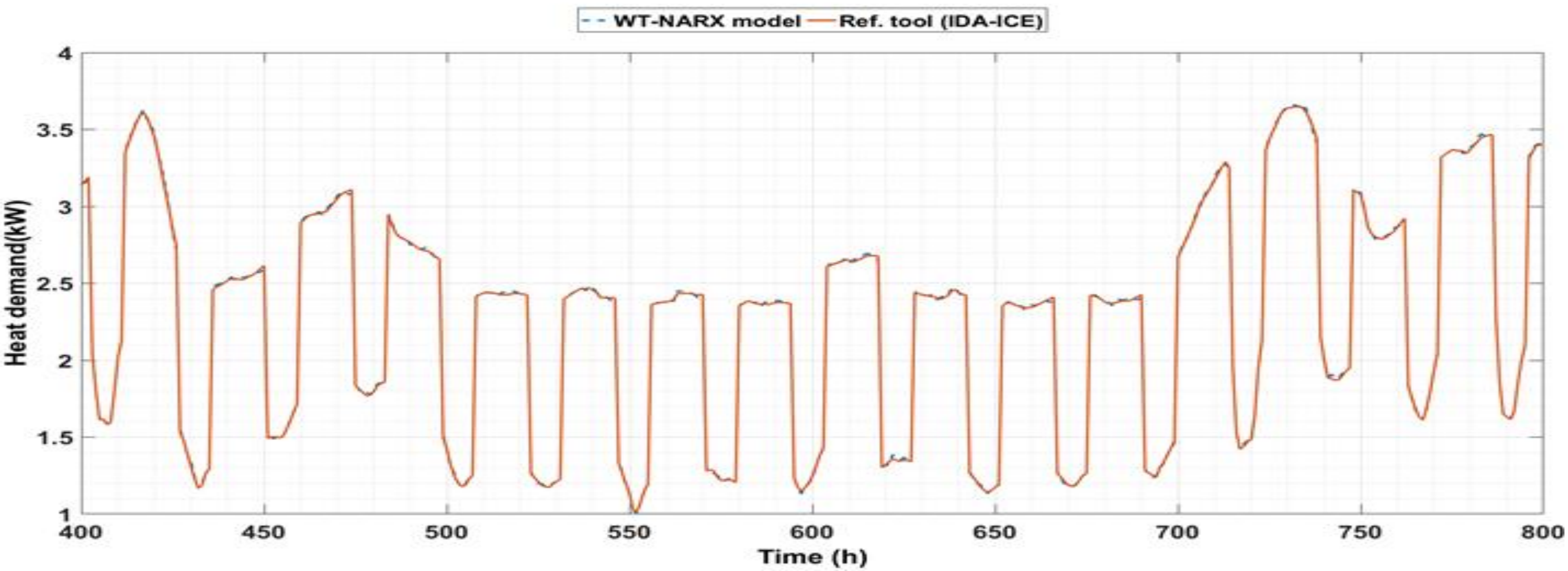




Item	***MSE training stage [kW]***	***R training stage***	***MSE prediction stage [kW]***	***(R) prediction stage***
WT-NARX	1.25×10^{-4}	99.90	1.24×10^{-3}	99.80
B-NARX	1.45×10^{-3}	97.3	2.53×10^{-1}	95.10


B-NARX model
Ref. tool (IDA-ICE)
Heat demand(kW)
Time (h)
0.5
1
1.5
2
2.5
3
3.5
4
400
450
500
550
600
650
700
750
800


WT-NARX model
Ref. tool (IDA-ICE)
Heat demand(kW)
Time (h)
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1.5
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400
450
500
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800

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Objective

$$minimize\ \left(\sum_{i=1}^{24}(price)(\mathrm{Demand})\right)$$

- Price is available by released data by market
- Heat demand has been forecasted by predective model.

By above information, it is possible to run an optimization package.

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- Linear programing is classical tool to find optimal solutions of linear problems.
- Daily heating energy cost can be defined as linear cost function.

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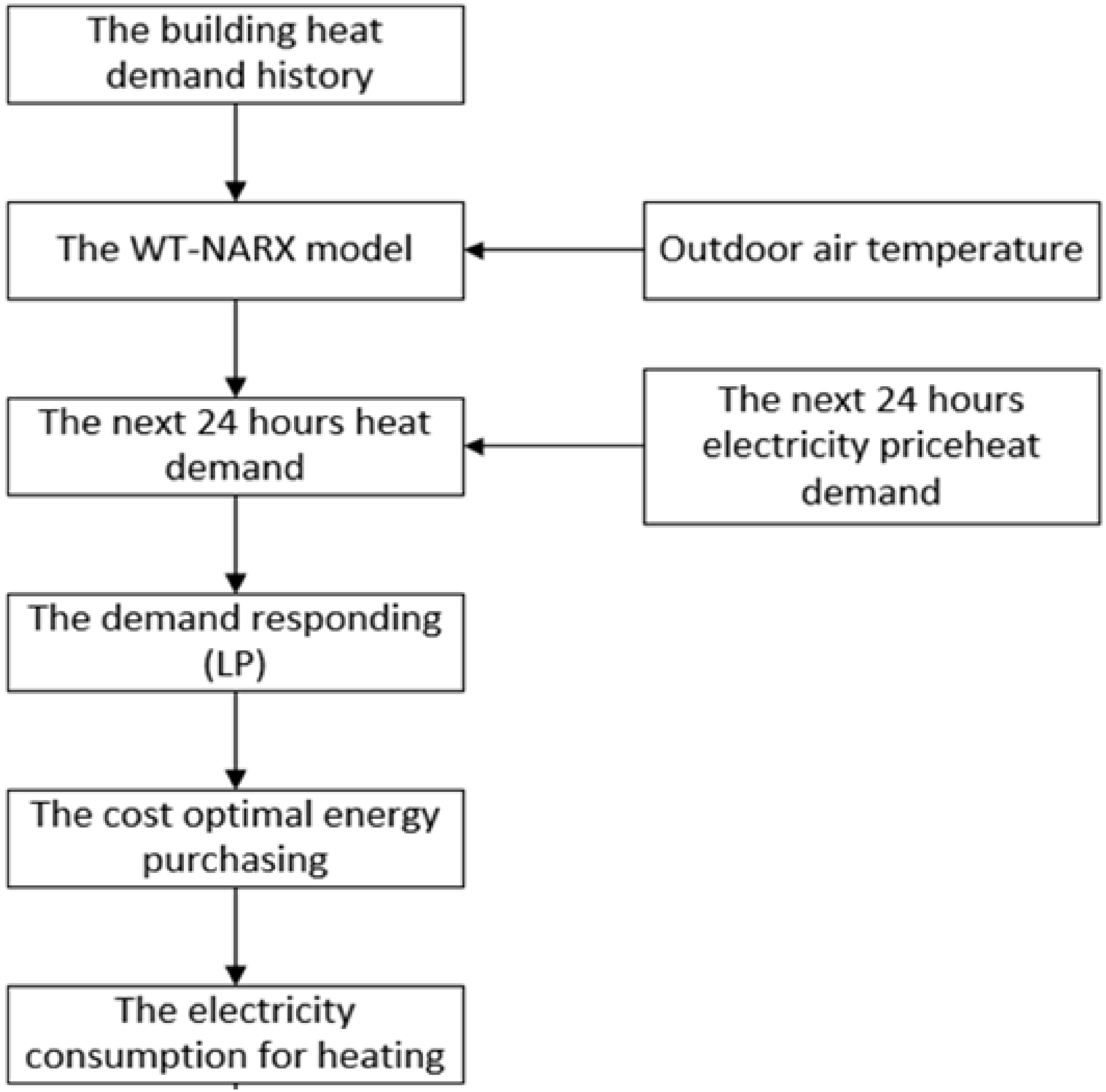
Matlab Toolbox


The building heat demand history
The WT-NARX model
Outdoor air temperature
The next 24 hours heat demand
The next 24 hours electricity priceheat demand
The demand responding (LP)
The cost optimal energy purchasing
The electricity consumption for heating

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Item *(control structure)*	*WT-NARX + LP*	*B-NARX + LP*	*Without DR control* *(the reference case)*
Annual electricity cost (€/m², a)	*1.4*	*1.5*	*1.6*
Annual purchased electricity (kWh/ m², a)	*13.5*	*13.5*	*13.5*
Cost Reduction % *(compare with the reference state)*	*12.5*	*6.3*	*-----*

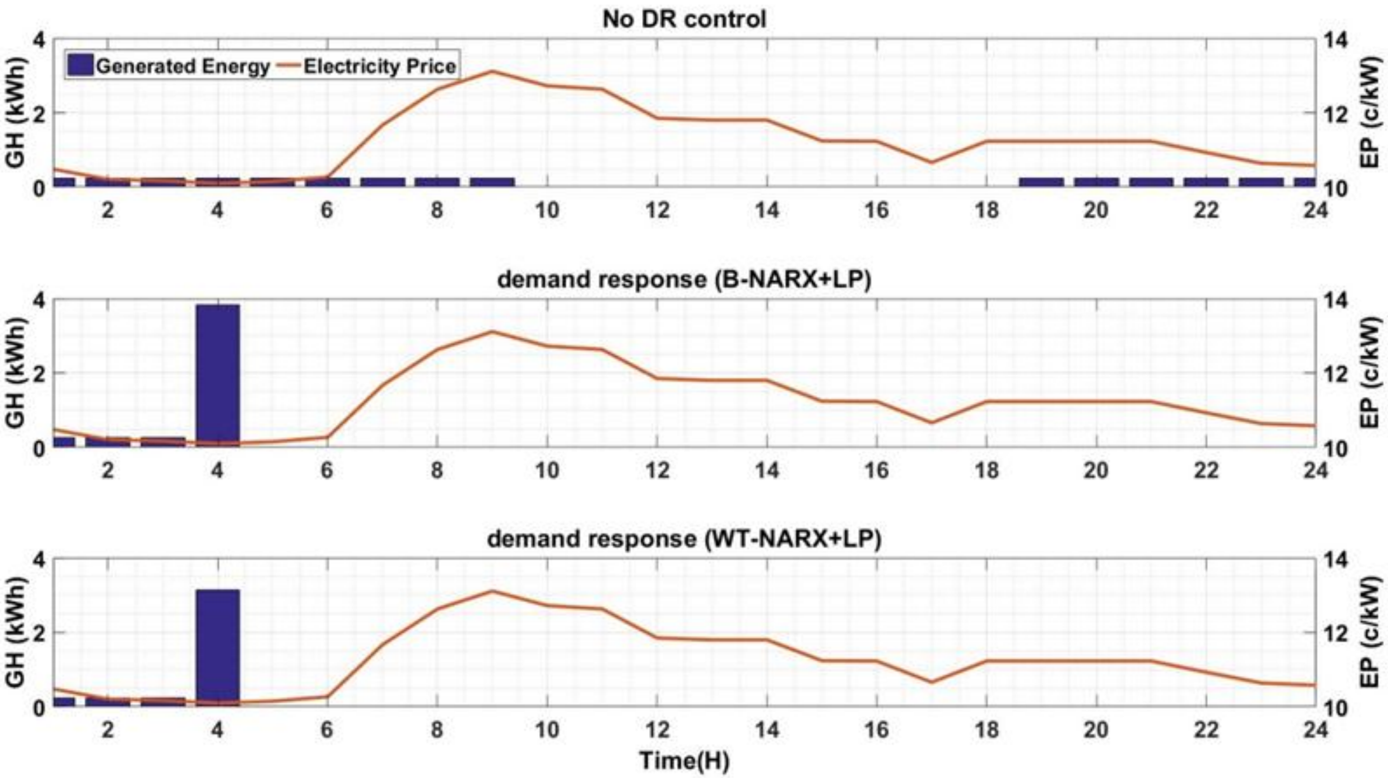
The heat demand of buildings can be predicted by means of an integrated NARX and a WT with high accuracy.

Using the predicted values of heat demand and future electricity price creates the opportunity to use the simple form of LP to optimize the operation of the heating system.

Mismatch between prediction and real heat demand reduces the performance of the proposed predictive DR control.

Thank you

Applying the control



$$minimize\ C_{T,h} = \sum_{i=1}^{H}(p_{el,i})(E_{h,s,i}/COP) \quad For\ \forall\ i \in [1,2 \ldots .24]$$

subject to

$$\sum_{i=1}^{j}(E_{h,s,i} - E_{h,d,i}) \geq 0 \quad For\ \forall\ j, i \in [1,2 \ldots .24],$$

$$\sum_{i=1}^{j}(E_{h,s,i} - E_{h,d,i}) < E_{h,s,max} \quad For\ \forall\ j, i \in [1,2 \ldots .24],$$

$$\sum_{i=1}^{H} E_{h,s,i} = E_{h,day} \quad For\ \forall\ i \in [1,2 \ldots .24],$$

$$0 \leq\ E_{h,s,i} \leq\ Q_{hp,h,max}(\Delta t) \quad \Delta t = 1hr\ and\ For\ \forall\ i \in [1,2 \ldots .24],$$