



# Artificial Neural Networks (ANN) modeling of the pulsed heat load during ITER CS magnet operation

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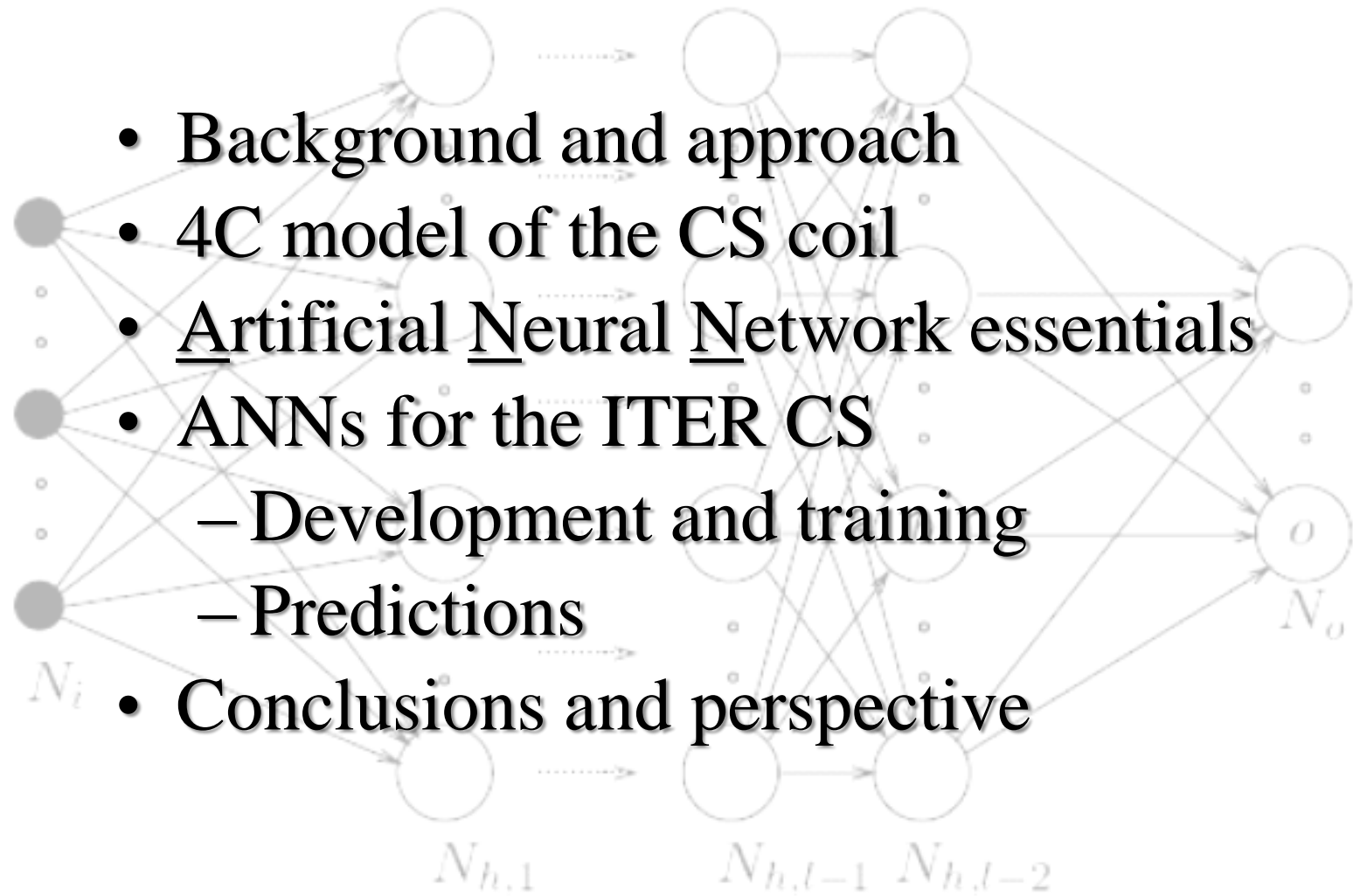
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*Work performed under ITER IO contract ITER/CT/12/430-554*

*The views and opinions expressed herein do not necessarily reflect those of the ITER Organization.*



# Outline





# Background (I)

The pulsed heat load to the cryoplant is an issue in tokamak inductive scenarios (rapid load variation, large power)



Smoothing of the heat load addressed experimentally (*HELIOS* loop at CEA Grenoble, France) and numerically (*4C code*,...)



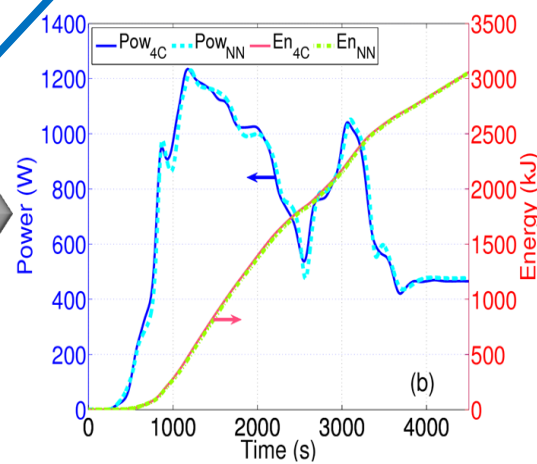
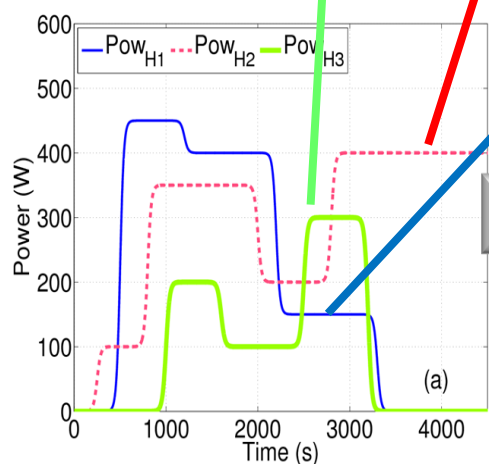
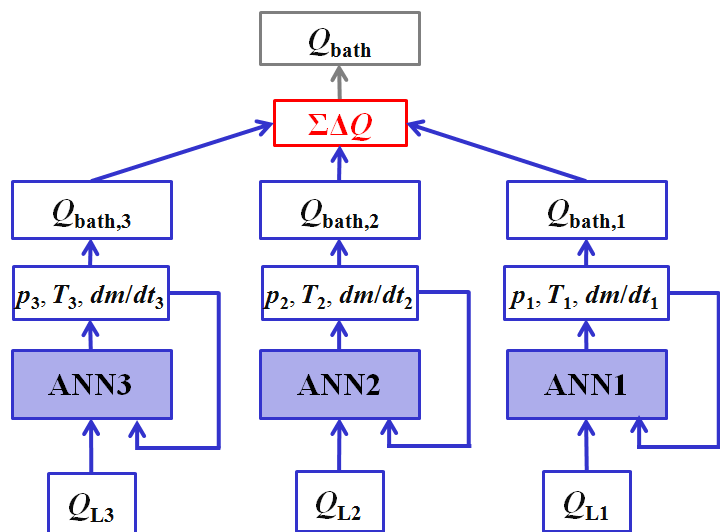
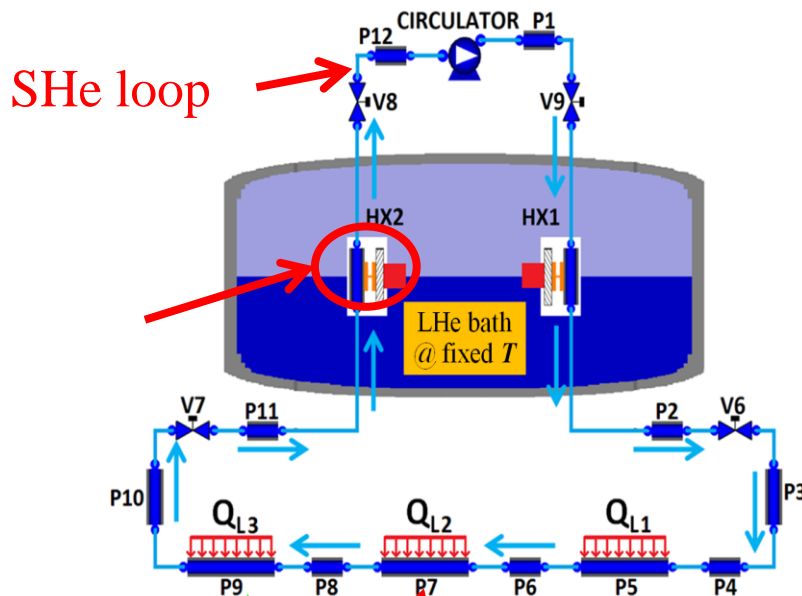
*... “only”  $Q(t)$  from magnets to LHe baths is required for the assessment of the cryoplant operation*



# Background (II)

[L. Savoldi Richard et al., Cryogenics, 2013]

- Dynamic response of the loop very well **predicted** by the 4C code
- Develop simplified but fast **Artificial Neural Networks** to predict the dynamic heat load to the LHe bath, **training/testing the ANN against the 4C results**



Chats

Accuracy:  $\varepsilon_{ave} \sim 1\%$ ,  $CPU_{4C} / CPU_{ANNs} \sim 100$



# Our approach

Use the 4C code to train and validate simplified but fast **Artificial Neural Networks**



Apply to ITER TF coils

Apply to ITER CS coils



Check flexibility, accuracy and speed on *HELIOS* loop



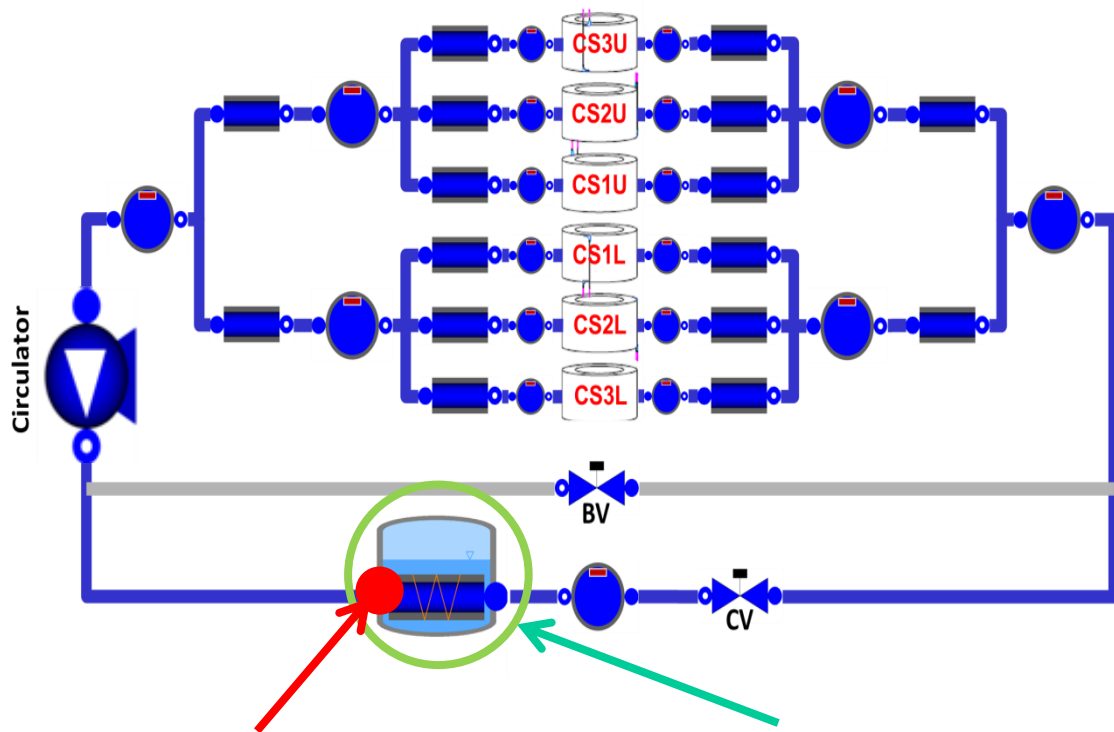
Develop ANN model to estimate heat load on LHe bath

[L. Savoldi Richard et al, Cryogenics, 2013]



# ITER CS coil

## 4C MODEL



*LHe bath @ constant temperature → power evolution at the HX only depends on inlet conditions*

*HX to LHe bath*

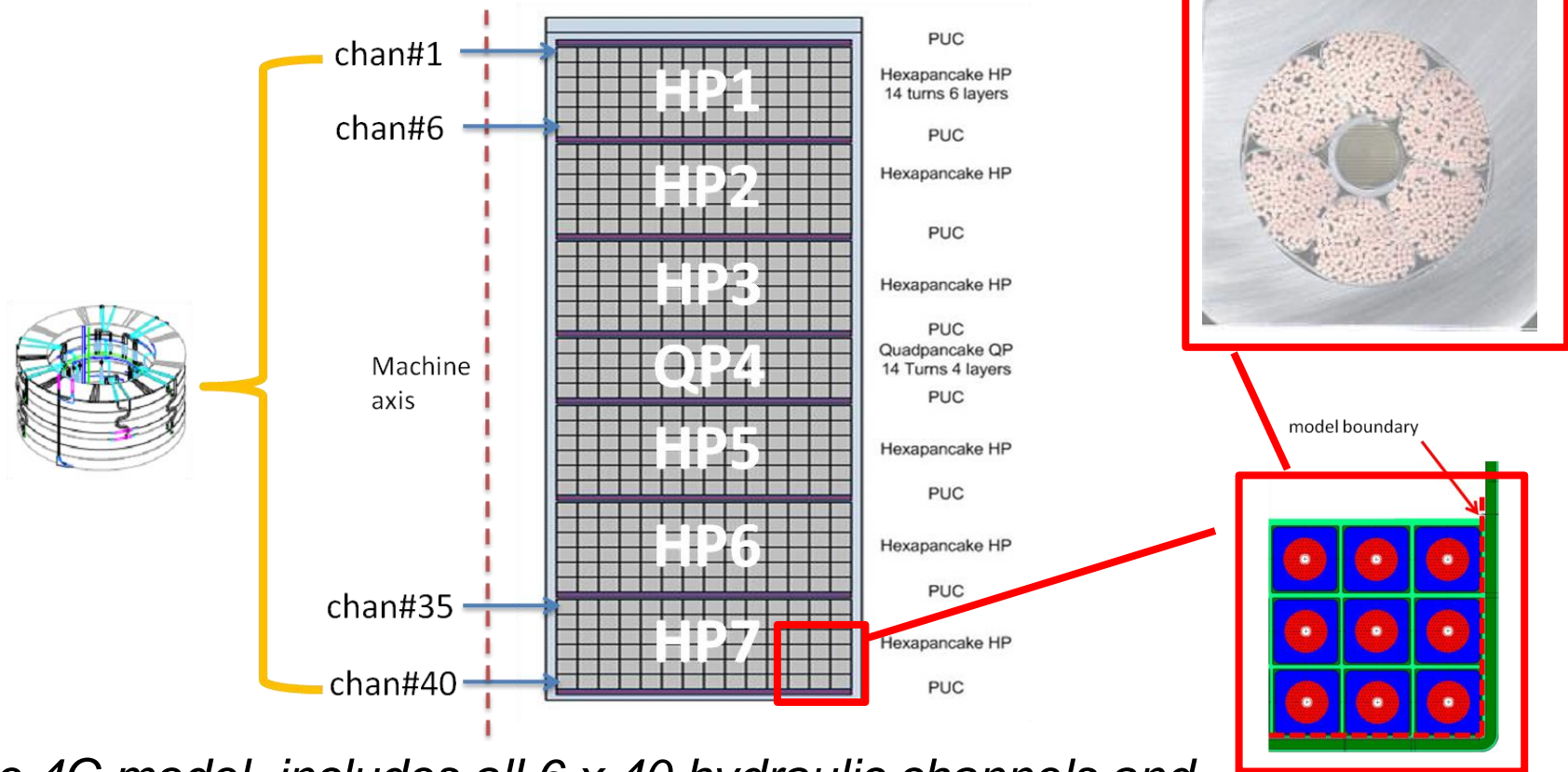
- Drivers = AC losses induced by current operation
- Dynamic response of the coil and of its cryogenic circuit can be predicted by the 4C code → Use 4C simulations to train and validate the ANN to predict power evolution at the HX





# ITER CS winding pack

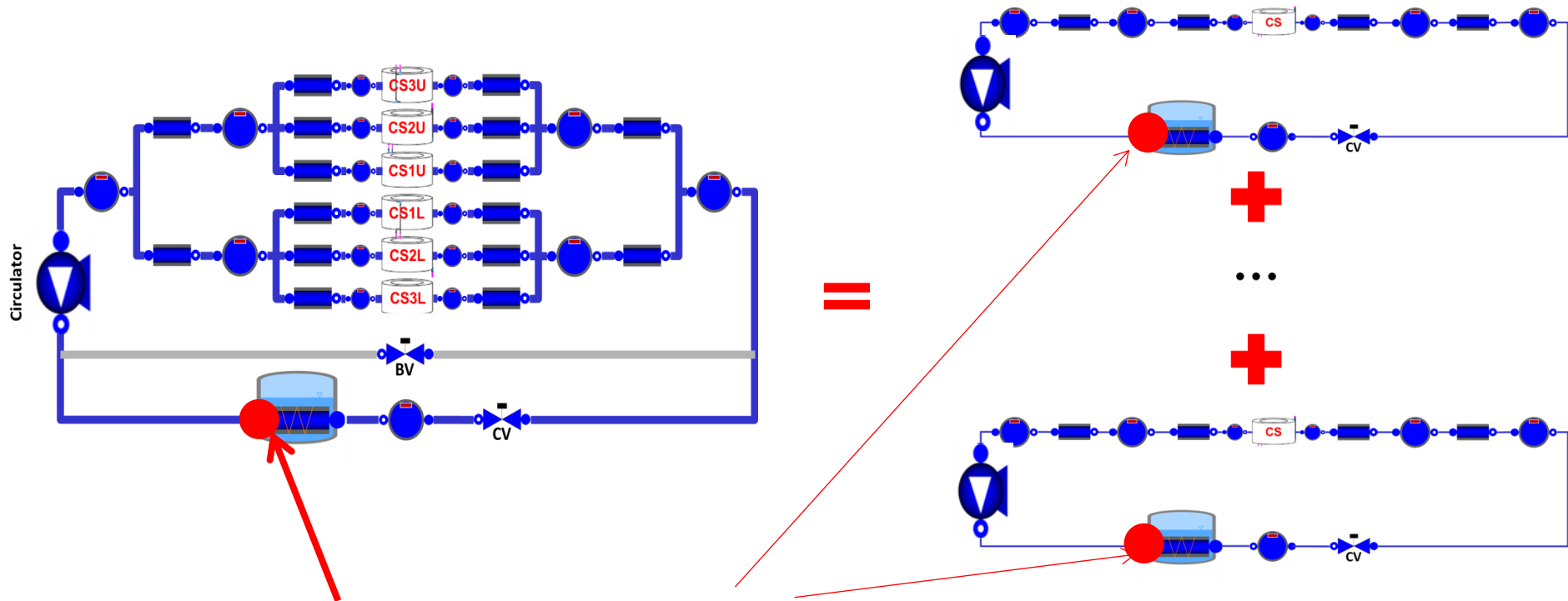
## 4C MODEL



*The 4C model includes all 6 x 40 hydraulic channels and their thermal coupling all along the winding pack*



# ITER CS coil: superposition of single modules



*$T(t)$ ,  $p(t)$  and  $dm/dt(t)$  at the HX inlet for whole CS coil can be well approximated by weighted sum of  $T(t)$ ,  $p(t)$  and  $dm/dt(t)$  obtained in partial models for each single module, with rescaled circuit*



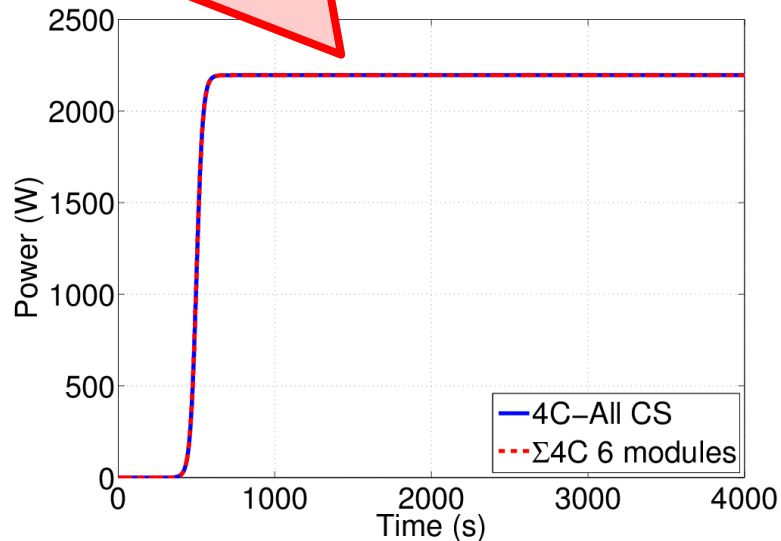




# Superposition verification

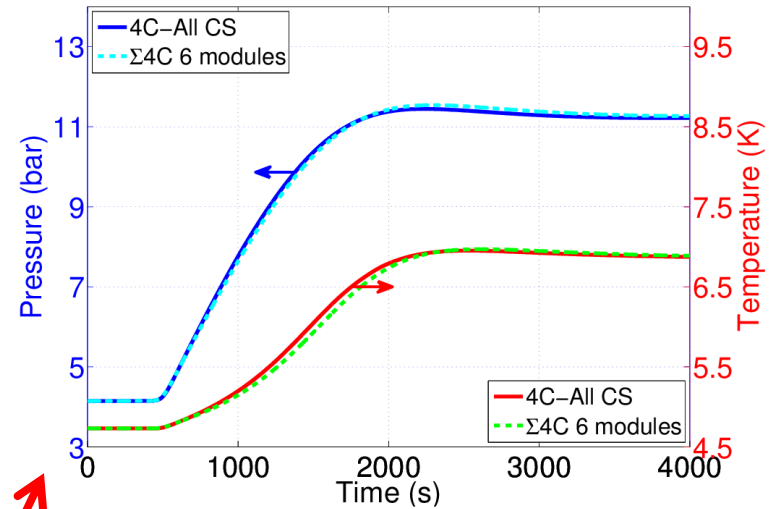
Apply same driver = sigmoid heating

- in all CS modules simultaneously
- in single modules (with rescaled circuit)

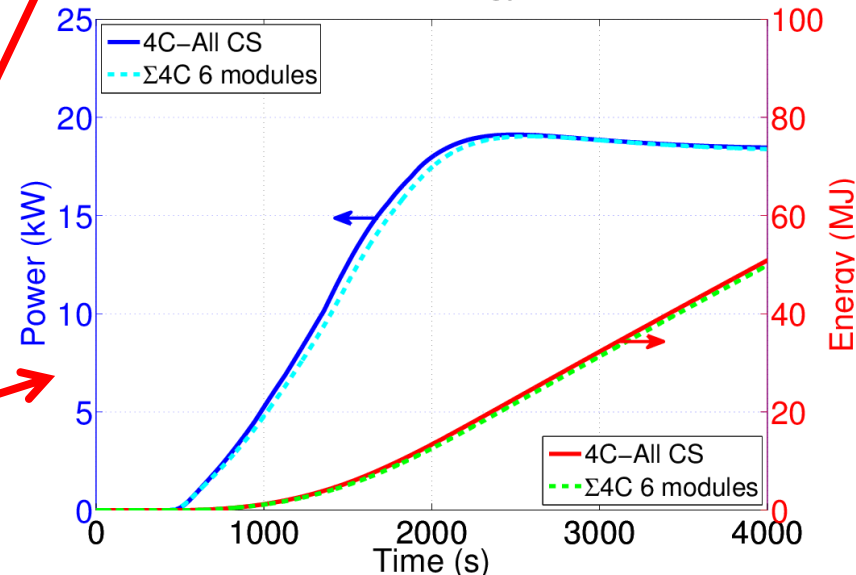


The whole CS dynamics can be obtained by superposition of single module  
→ Develop an ANN for each module

Pressure and Temperature @HX



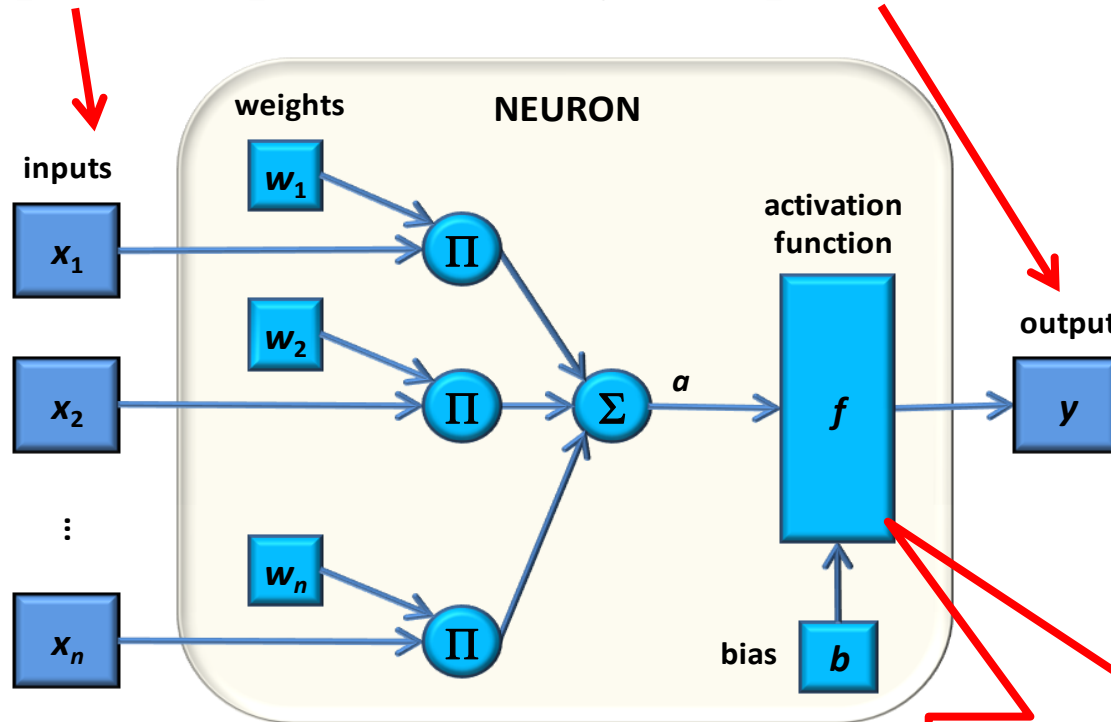
Power and Energy @HX





# ANNs (I). Artificial neuron

- In analogy with the brain neurons, combine more inputs  $x$  to produce a single output  $y$



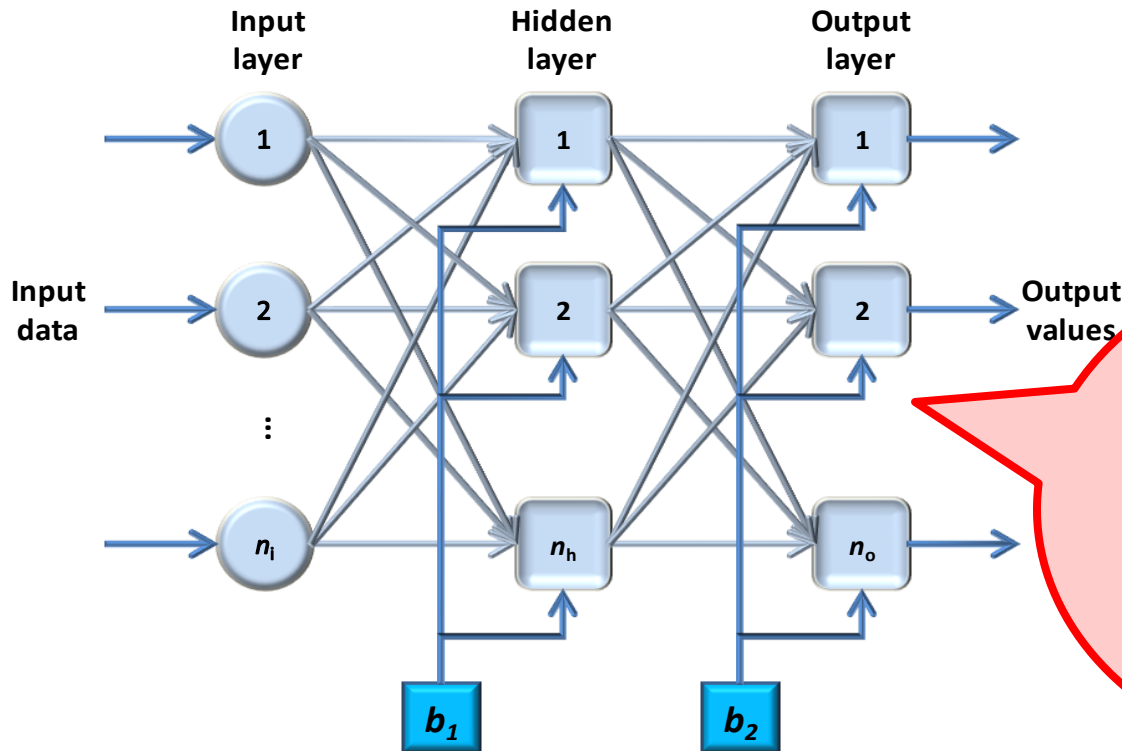
*Transfer function*

$$y = f\left(\sum_{i=1}^n w_i x_i - b\right)$$



# ANNs (II). “Learning” network

- Combine several neurons together to build a network



No physics content, except for the proper choice of input and output variables!

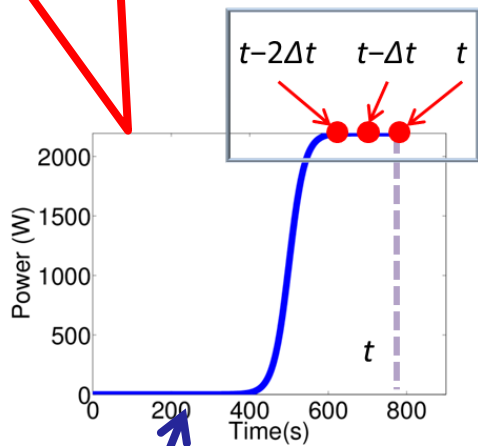
- “**Train**” the network = feed inputs & outputs to evaluate weights and biases through suitable training algorithms.



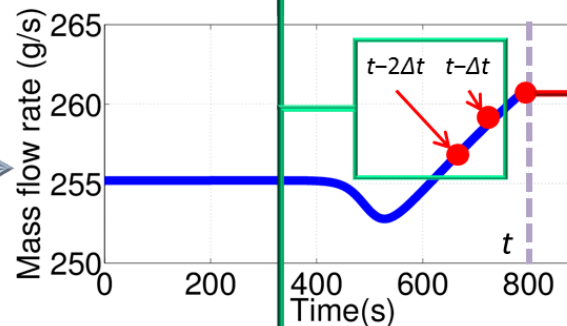
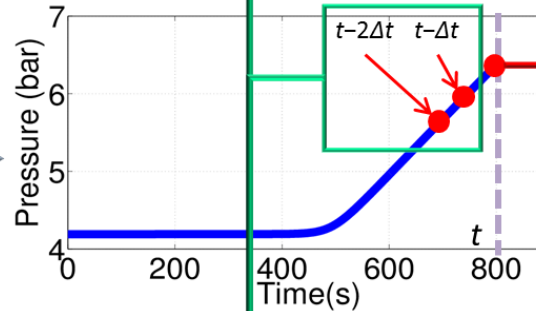
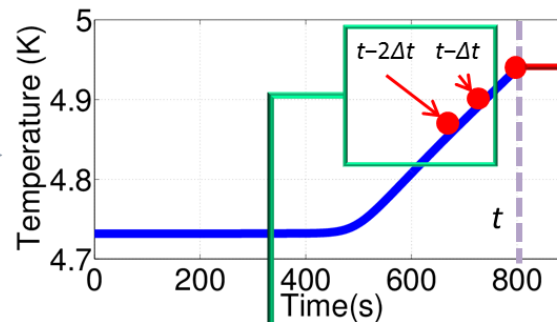
# Single ANN development and training: CS1U

- For each CS module develop a single ANN

**INPUT =  $Q(t)$  in  
one CS module**



**Feedback**



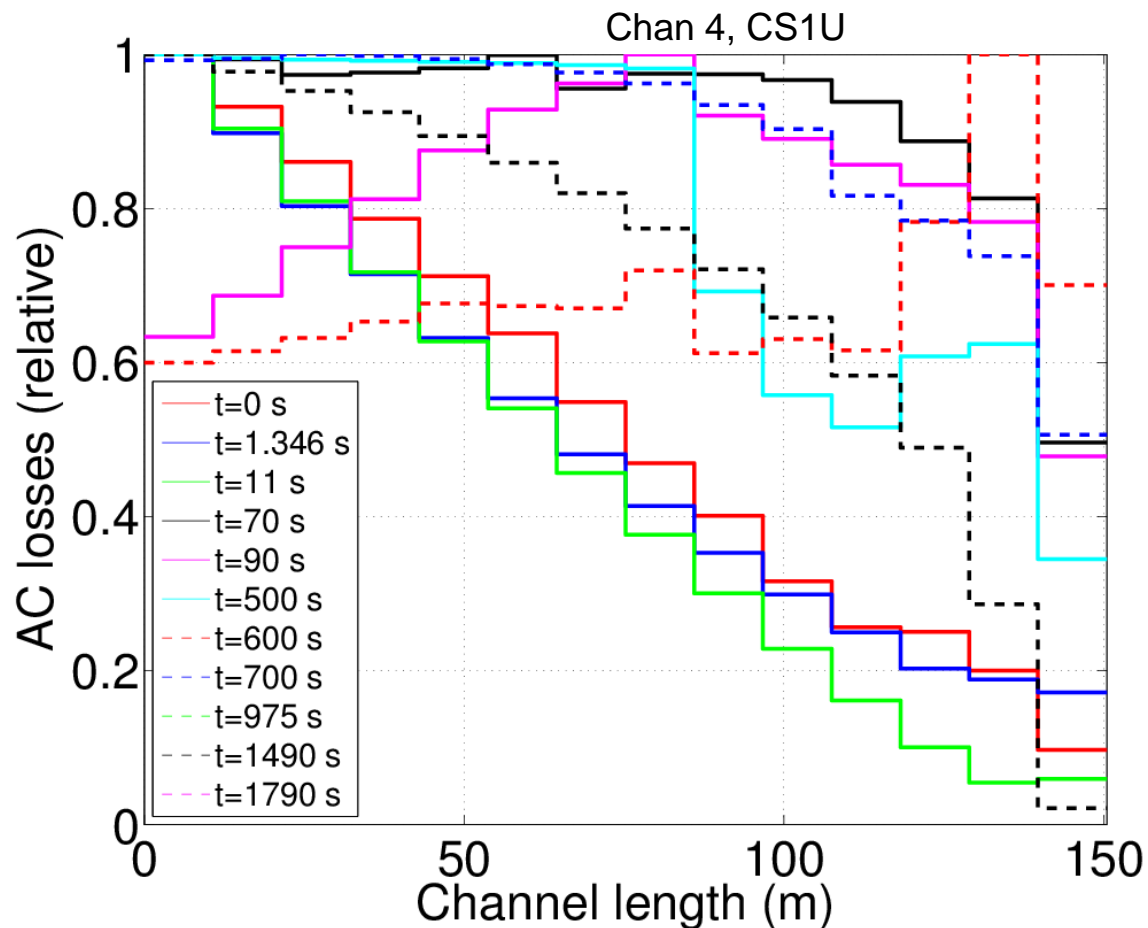
**OUTPUT =  
 $p(t)$ ,  $T(t)$  and  
 $dm/dt(t)$  at the  
HX inlet**

*Train the network with  
4C simulations, scanning  
the input power range  
[200W-4000W]*



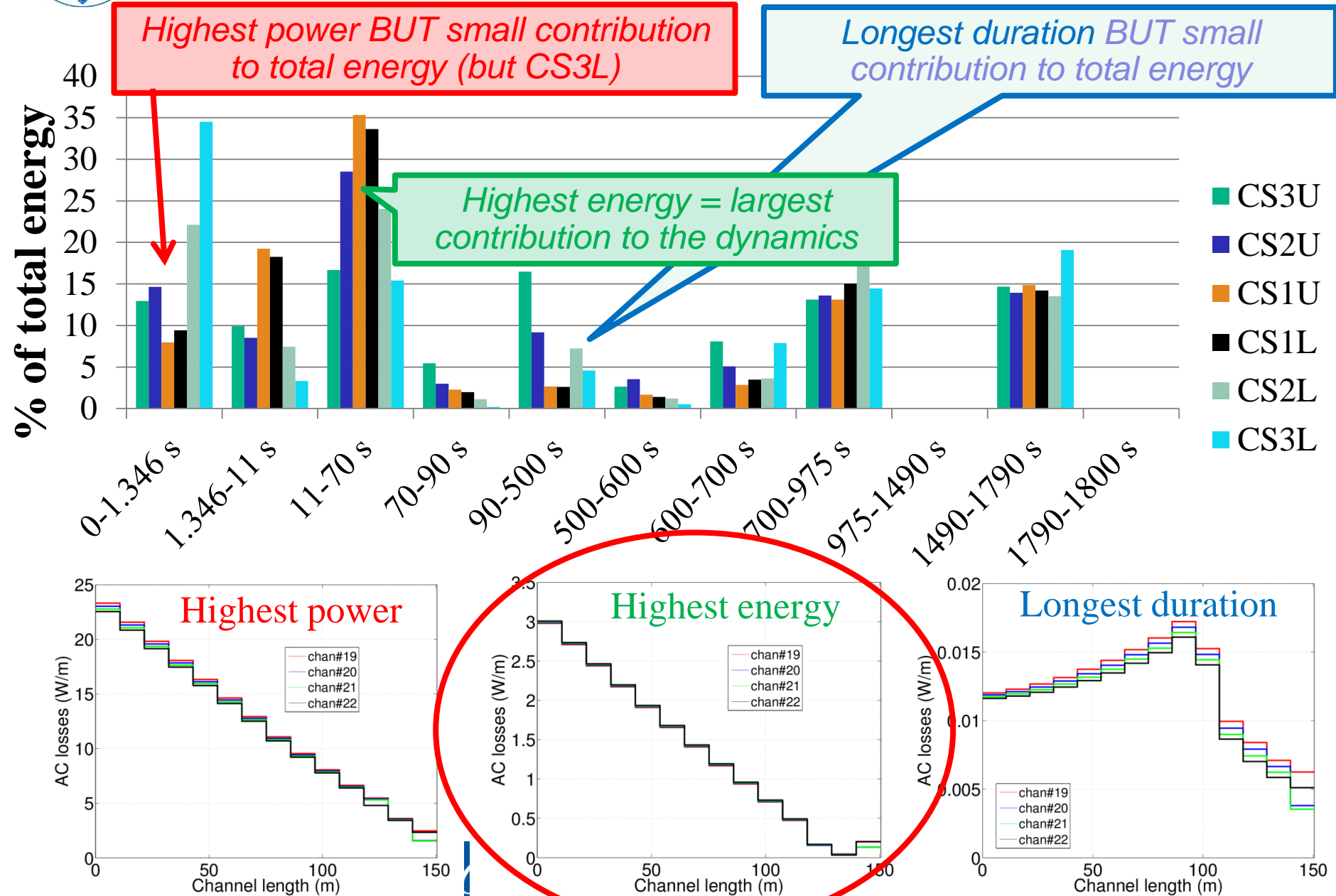
# Training process (I)

- Distribution of power density changes in space and time along each hydraulic channel
- Choice of most suitable power distribution?





# Training process (II)

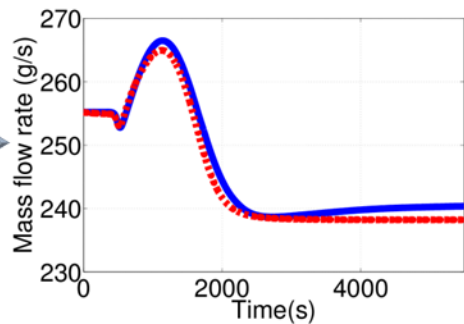
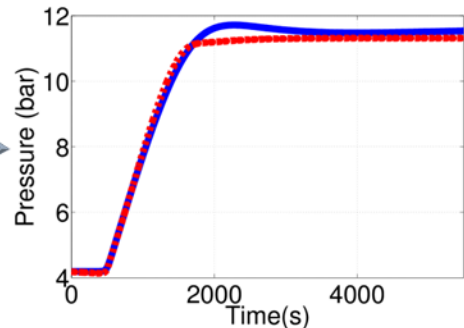
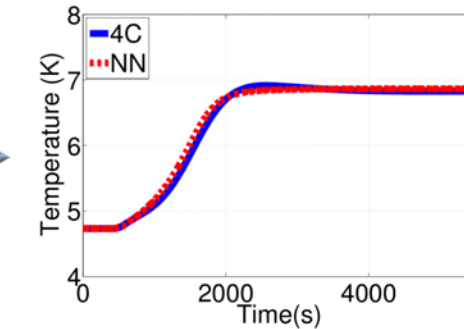
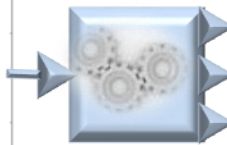
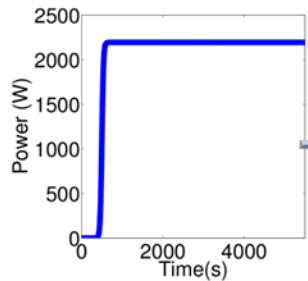




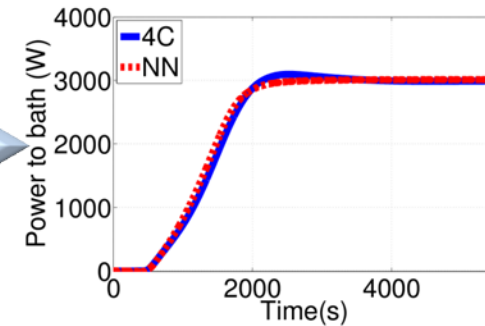


# Single ANN prediction: simple waveform on CS1U

*SIMPLE heater  
waveform*



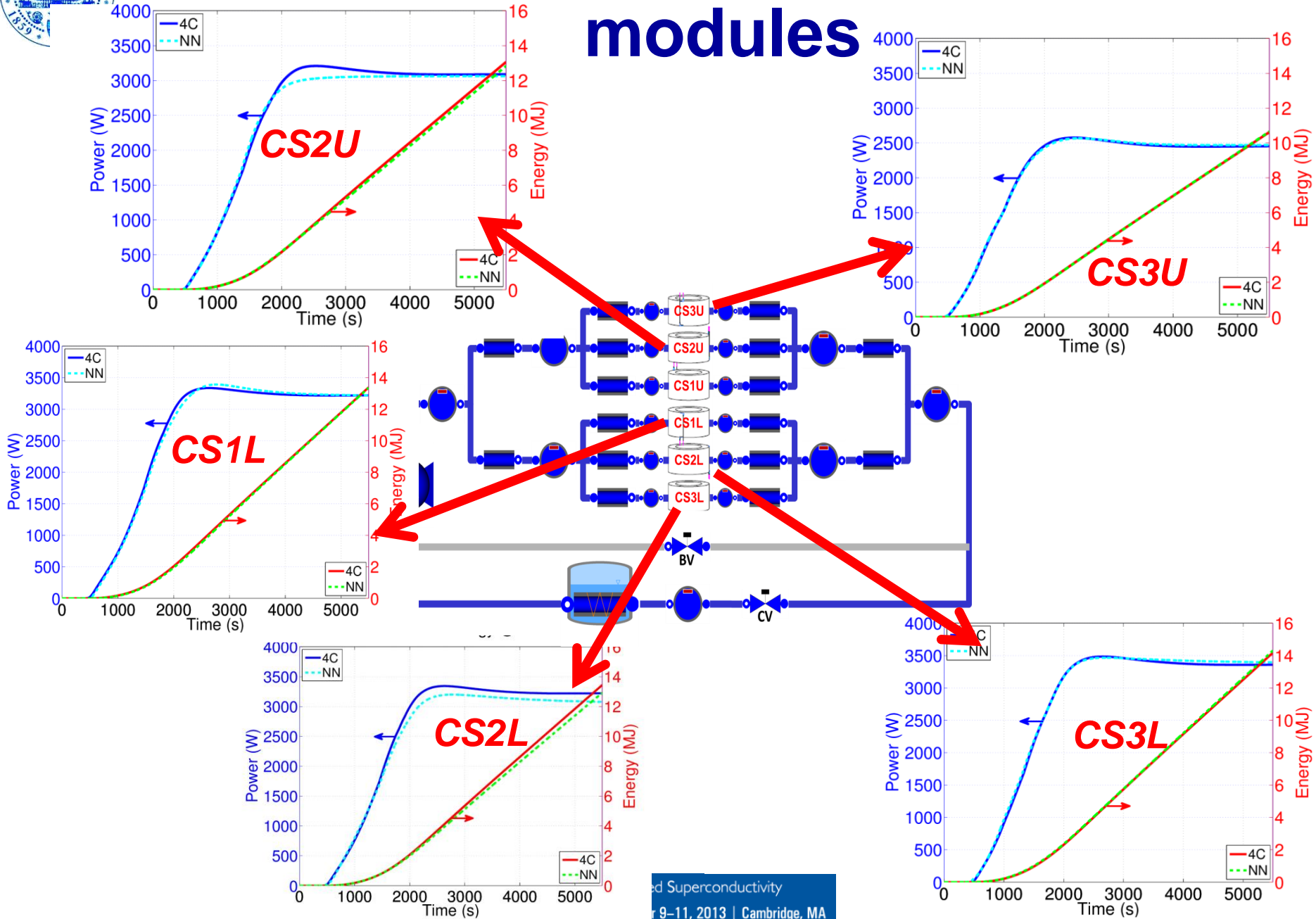
$$Q = \frac{dm}{dt} \times (h(p,T) - h_0)$$



- ANN predictions in very good agreement with 4C simulations in cases never seen in the training
- $CPU_{4C} / CPU_{ANN} \sim 25000!$



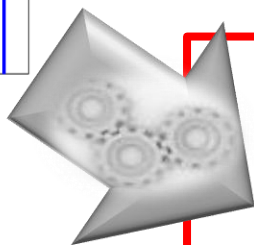
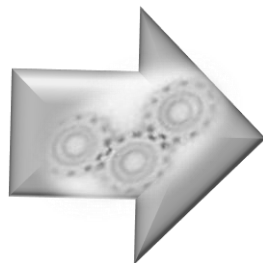
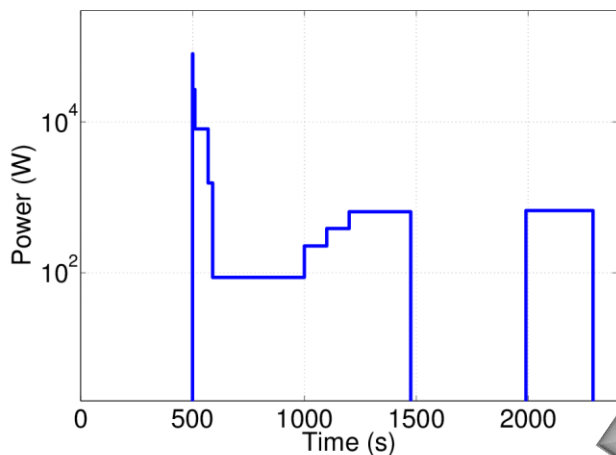
# Single ANN prediction on other modules



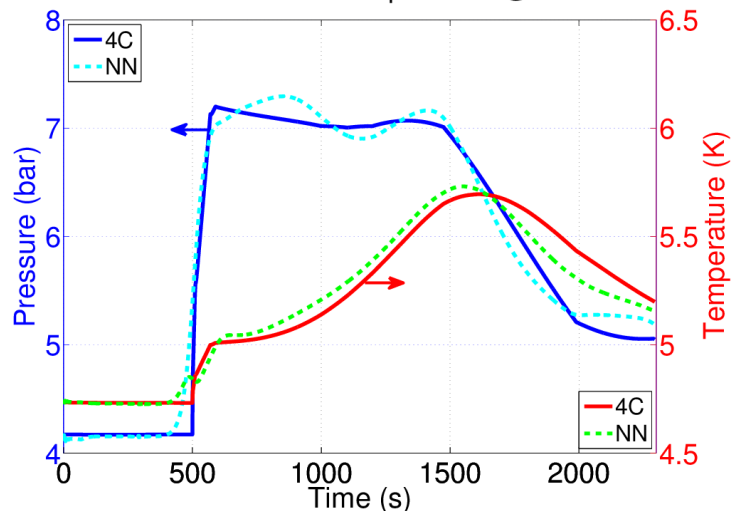


# Single ANN prediction: ITER-like waveform on CS1U

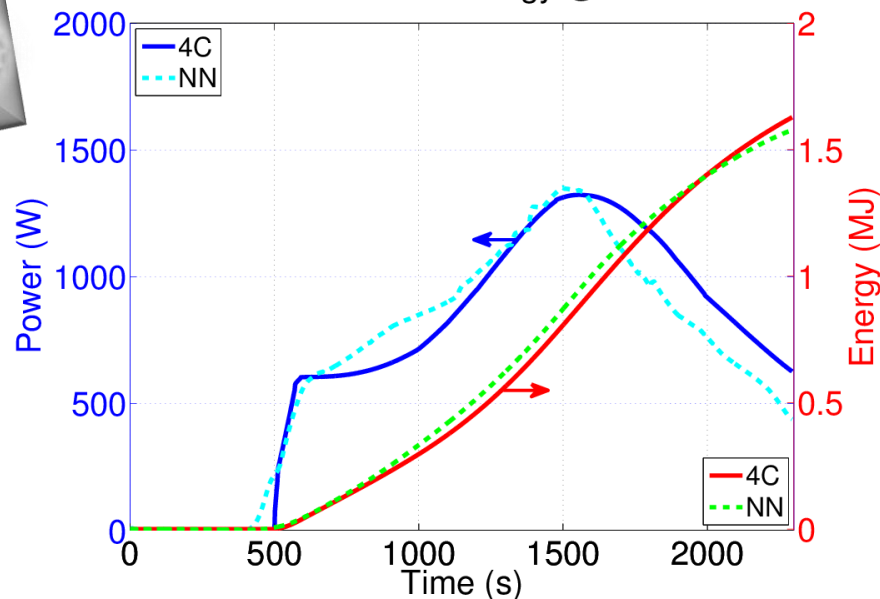
*GENERAL  
heater waveform*



Pressure and Temperature @HX



Power and Energy @HX

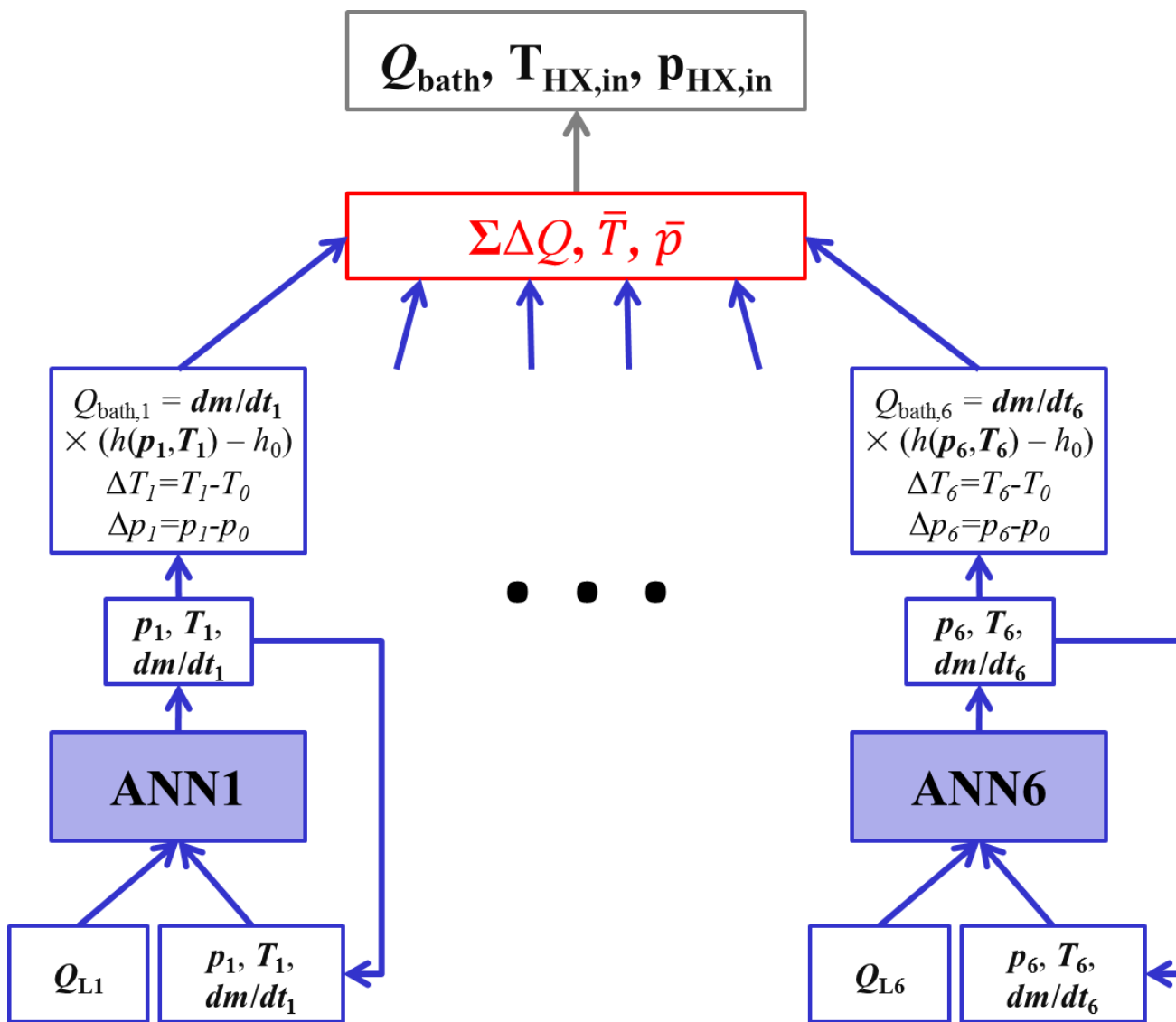


$$\varepsilon_{ave} \sim 13\%, \varepsilon_{peak} \sim 3\%$$

$$CPU_{4C} / CPU_{ANNs} \sim 4000$$

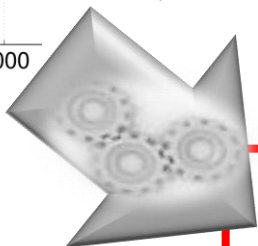
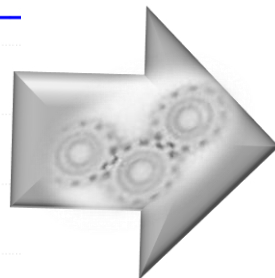
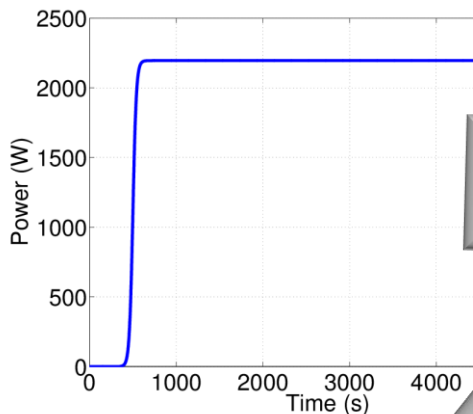


# From single module back to CS coil

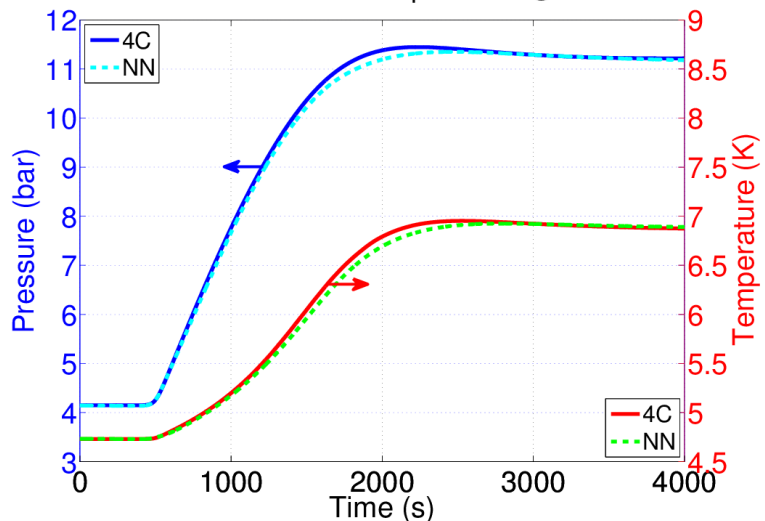




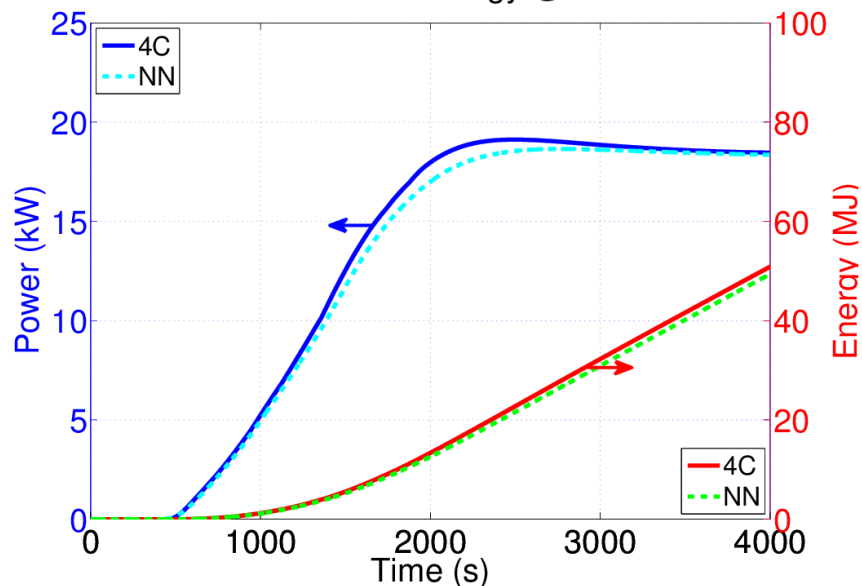
# CS coil prediction: simple waveform



Pressure and Temperature @HX



Power and Energy @HX

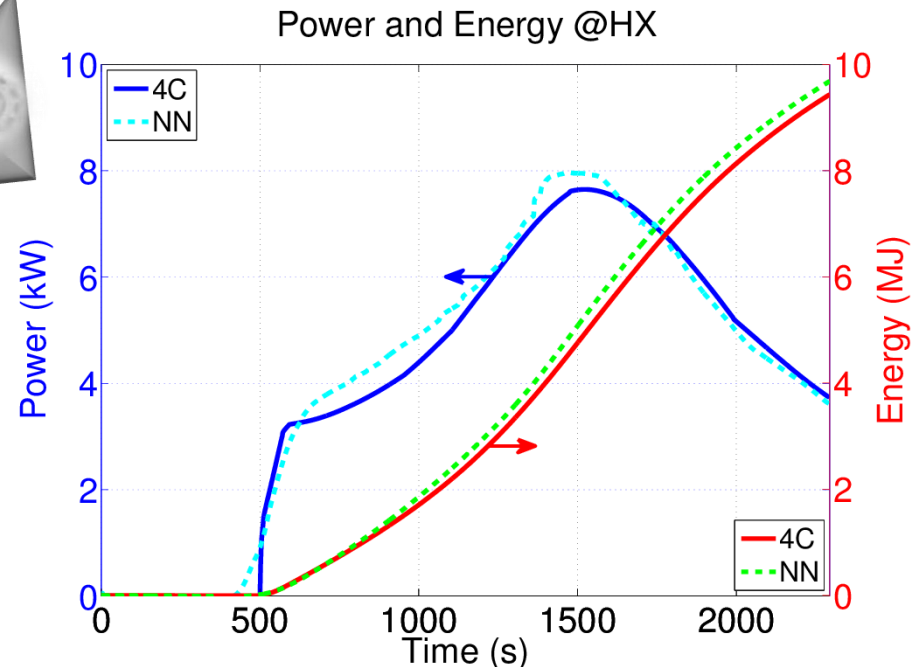
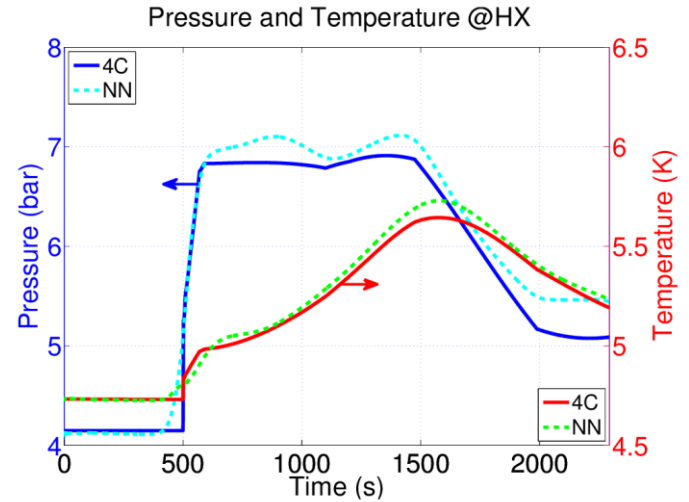
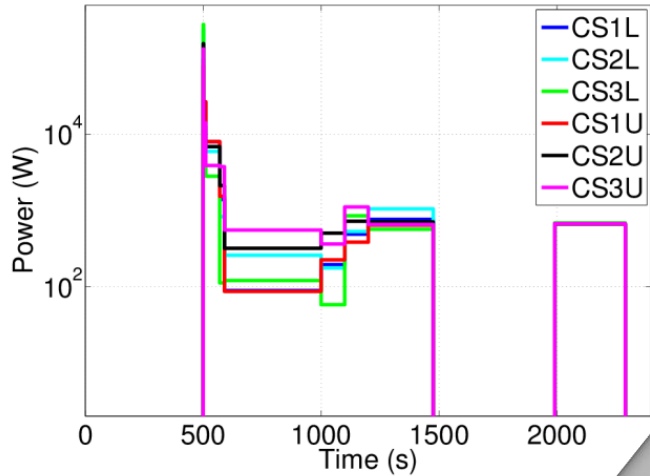


- Very good accuracy:

$$\varepsilon_{ave} \sim 3.3\%$$

-  $CPU_{4C} / CPU_{ANNs} \sim 12000$

# Final prediction: waveform from plasma operation scenario on the whole CS coil



- Very good accuracy:  $\varepsilon_{ave} \sim 5.9\%$
- $CPU_{4C} / CPU_{ANNs} \sim 500$   
(ANN faster than realtime!)





# Conclusions

- Recently proposed approach to the simplified model of heat load on LHe bath through ANNs has been successfully applied to the ITER CS
- The ANN model for the CS dynamic response developed and trained against data from the 4C code proved to be:
  - Flexible
  - Accurate
  - Fast (faster than realtime!)





# BACKUP SLIDES



# Accuracy and speed

	# of sigmoids	$t_{4C}/t_{NN}$	Average error (%)	Error at peak (%)
<b>CS1L</b>	70	3600	15.6	10.4
<b>CS2L</b>	136	1856	14.3	0.6
<b>CS3L</b>	154	1600	22.7	7.6
<b>CS1U</b>	66	3789	12.8	1.4
<b>CS2U</b>	102	2440	13.4	7.7
<b>CS3U</b>	92	2667	13.9	8.9
<b>All CS</b>	620	500	5.9	3.9