Artificial Neural Network modeling of heat transfer problems at the interface between different subsystems of a superconducting tokamak

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Outline

- **Context**
- **Heat transfer at interfaces**
- **Objective 1**
  - Artificial Neural Network essentials
  - ANN models development
  - Application to ITER magnets
- **Future work: Objective 2**
The NFE research group @ PoliTo keeps developing computational tools/methods focused on heat transfer/thermal-hydraulics.

Well-established international collaborations: F4E Barcelona, ITER IO Cadarache, CEA Grenoble, CEA Saclay, IPP Greifswald, KIT Karlsruhe, NFRI Daejon, CAS Hefei, JAEA Naka.

**HERE:** emphasis on the HEAT TRANSFER problems at the interfaces (e.g., superconducting magnets-cryoplant, plasma-first wall, ...), very relevant for a tokamak operation.
An accurate and reliable prediction of the heat fluxes on plasma facing components (PFC) is still an open and critical issue.
Objective 1: Simplified modeling of magnet-cryoplant heat transfer

Predict the thermal load $Q_{th}(t)$ to the cryoplant (*check operating scenarios, optimize operation*).

Options:

- **4C code** [L. Savoldi Richard et al, *Cryogenics, 2010*]. Detailed tool, high computational effort!
- Simplified models
- **💡 Simplified Artificial Neural Network (ANN) models**: less accurate but fast!
Artificial Neural Network essentials

- Combine several neurons together to build a network

\[ \text{Input data} \rightarrow \text{Hidden layer} \rightarrow \text{Output layer} \]

Physics content provided by the network training!

- "Train" the network = feed inputs & outputs to evaluate weights and biases through suitable training algorithms.
ANN models development

Combined strategy = use the validated 4C code [R. Zanino et al, Cryogenics, 2013] to train and test the ANN

STEP 1

ANN model1 → predict the dynamic heat load to the LHe baths to check operation scenarios

Heat transfer

STEP 2

Strategy VALIDATION on “simple” case

Application to ITER magnets

ANN model2 → predict the dynamic response (T, dm/dt) at the outlet of the magnet also including possible control and regulation (→ optimize operation)
Validation of the 1st step

Dynamic response of the HELIOS loop very well predicted by the 4C code

Based on 4C results train&test ANN Model_1

HELIOS loop (CEA Grenoble)

Very simple and efficient BUT only works without control/regulations

Accuracy: $\varepsilon_{\text{ave}} \sim 1\%$

Speed: $\sim 100 \times$
Validation of the 2\textsuperscript{nd} step

[S. Carli et al., “Incorporating Artificial Neural Networks in the dynamic thermal-hydraulic model of controlled cryogenic circuits”, submitted to Cryogenics, 2014]

When \textbf{controls/regulations} act on the cooling loop and the LHe bath

\textbf{Train\&test} ANN to substitute the heated line in 4C $\rightarrow$ predict the \textbf{dynamic} response ($T$, $\frac{dm}{dt}$) at the outlet of the heated line
Application to ITER CS coil

MODEL1

Heat transfer

Inputs

15MA scenario

Power and Energy @HX

Speed ~ 500 x
(ANN model_1 faster than realtime!)

Application to ITER CS coil

15MA scenario

Development of ANN model_2 with control/regulation is ongoing
Application to ITER TF coil

15MA-14kW scenario

1st step

Application to ITER TF coil

15MA-14kW scenario

\[ \varepsilon_{\text{peak,W}} \approx 6.8\% \]
\[ \varepsilon_{\text{peak,C}} \approx 6\% \]

Speed \(\approx 150 \times\) faster

ANN model_2 with control/regulation not complete

Future work: Objective 2 - simplified modeling of plasma-wall heat transfer

- Consider the set of modeling tools already available for the plasma-wall interactions and the thermal-fluid dynamic modeling of plasma-facing components (PFC).

- Assess feasibility of applying soft computing techniques to describe the heat loads to the PFC under the different plasma operating scenarios.
