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Artificial Neural Networks: a viable tool to design heat load smoothing strategies for the ITER Toroidal Field coils

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Abstract. In superconducting tokamaks, cryoplants provide the helium needed to cool the superconducting magnet systems. The evaluation of the heat load from the magnets to the cryopant is fundamental for the design of the latter and the assessment of suitable strategies to smooth the heat load pulses induced by the pulsed plasma scenarios is crucial for the operation. Here, a simplified thermal-hydraulic model of an ITER Toroidal Field (TF) magnet, based on Artificial Neural Networks (ANNs), is developed and inserted into a detailed model of the ITER TF winding and casing cooling circuits based on the state-of-the-art 4C code, which also includes active controls. The low computational effort requested by such a model allows performing a fast parametric study, to identify the best smoothing strategy during standard plasma operation. The ANNs are trained using 4C simulations, and the predictive capabilities of the simplified model are assessed against 4C simulations, both with and without active smoothing, in terms of accuracy and computational time.

1. Introduction

In the ITER tokamak, the low- T_c superconducting (SC) magnets will be cooled by supercritical helium (SHe); in particular, each magnet subsystem, among which the Toroidal Field (TF) coils, will have a dedicated cryogenic loop, that will eventually transfer the heat to the cryopant [1]. One of the main issues, from the point of view of the cryopant design, is the pulsed nature of the (inductive) tokamak operation, which makes the design load of the cryopant much higher than what is actually needed during most of the operation, leading to lower efficiency and higher costs. In order to smooth the heat load variation during the pulse, a saturated liquid helium (LHe) bath is used as a thermal buffer (see Figure 1), but, as this is still not enough, several active strategies to achieve this smoothing are being investigated [2, 3, 4].

Detailed thermal-hydraulic (TH) tools are already available for the transient analysis of the magnets operations, such as the 4C code [5], which has been tested against several transients from different magnets [6, 7], and validated against experimental data from the HELIOS loop [8, 9, 10] and from full-size magnet systems as well [11, 12, 13]. Unfortunately, the level of detail of such tools is paid in terms of computational effort, and they cannot be applied, for instance, for the real-time assessment and control of the cryopant operation, which however does not require such a level of detail about the magnets themselves.

Soft computing techniques, like Artificial Neural Networks (ANNs), were applied for the first time by our group to the problem of the cooling of the ITER SC magnets in the absence of controls, aiming



at the prediction of the evolution of the heat load to the cryoplant during standard plasma operation. In particular, the new technique was successfully applied to the operation of the HELIOS loop [14], as well as of the ITER Central Solenoid (CS) [15] and the ITER TF acting in nominal operating conditions [16], showing that ANNs are able, when suitably trained, to reproduce the experimental (HELIOS) and simulated (CS, TF coils) dynamics of the system and to lead to a fast and accurate evaluation of the heat load to the LHe baths.

Recently, the emphasis of this approach has been shifted to the demonstration of the capability of ANN-based models to reproduce the dynamics of cryogenics circuits where an active control of the cooling (regulation of the mass flow rate) is needed. This approach has been proved to work and validated against experimental and computed results in HELIOS [17] and it has been successfully applied to the controlled operation of the ITER CS [18]. However, as a main difference with respect to the ITER CS, in the case for the ITER TF coils a significant role in the system dynamics is played by radial plates in the winding pack and casing [19, 20]. The winding and the casing, subject to different heat loads acting during different phases of the plasma pulse, are thermally coupled through the ground insulation. For these reasons, the ITER TF requires a more sophisticated ANN model than that developed for the ITER CS [18].

Here we show how the ANN-based model of the ITER TF magnet winding pack and casing cooling, suitably embedded in the 4C TF circuit model where control/regulation of the cooling circuits can be achieved by, for instance, the opening of the bypass valve in the casing cooling loop (Figure 2), can be used to investigate and test control strategies for mitigation of the heat load from the coils to the cryoplant, as soon as the ANNs are suitably trained.

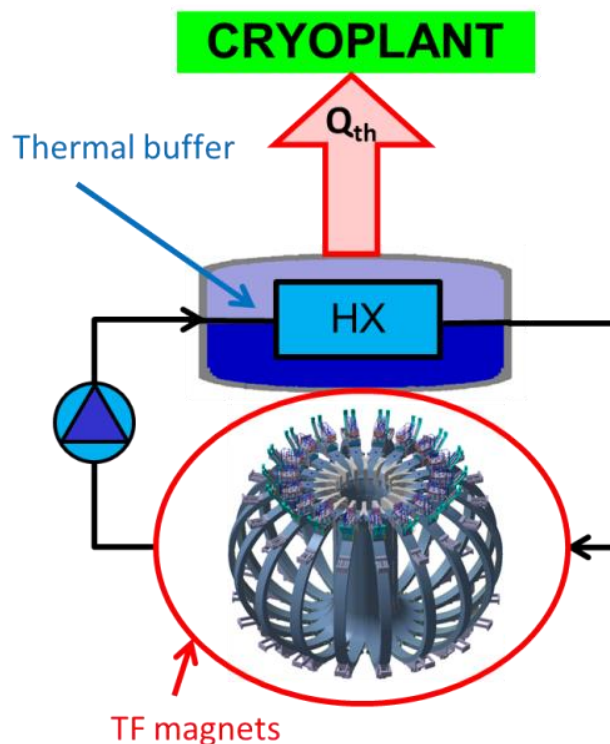


Figure 1. Schematic view of the cooling strategy of the ITER TF magnets. A heat exchanger (HX) releases the pulsed heat loads coming from the magnets during tokamak operation to a thermal buffer, which smooths the thermal load transferred to the cryoplant.

2. ANN model of the TF cooling loops

The ANN model used in the present work is shown in the inset in Figure 2, together with the 4C model of the two TF coil cooling circuits [19, 20]. The model has the same structure of that reported in [16]: in fact all the components are the same, with the exception of the ANNs, that must be trained in order to follow also a transient in which there is active control on the mass flow rate inside the coil.

All the ANNs are feed-forward networks: in fact, there is no need for a closed feedback loop, as the required information is provided to the network directly by the circuit [21].

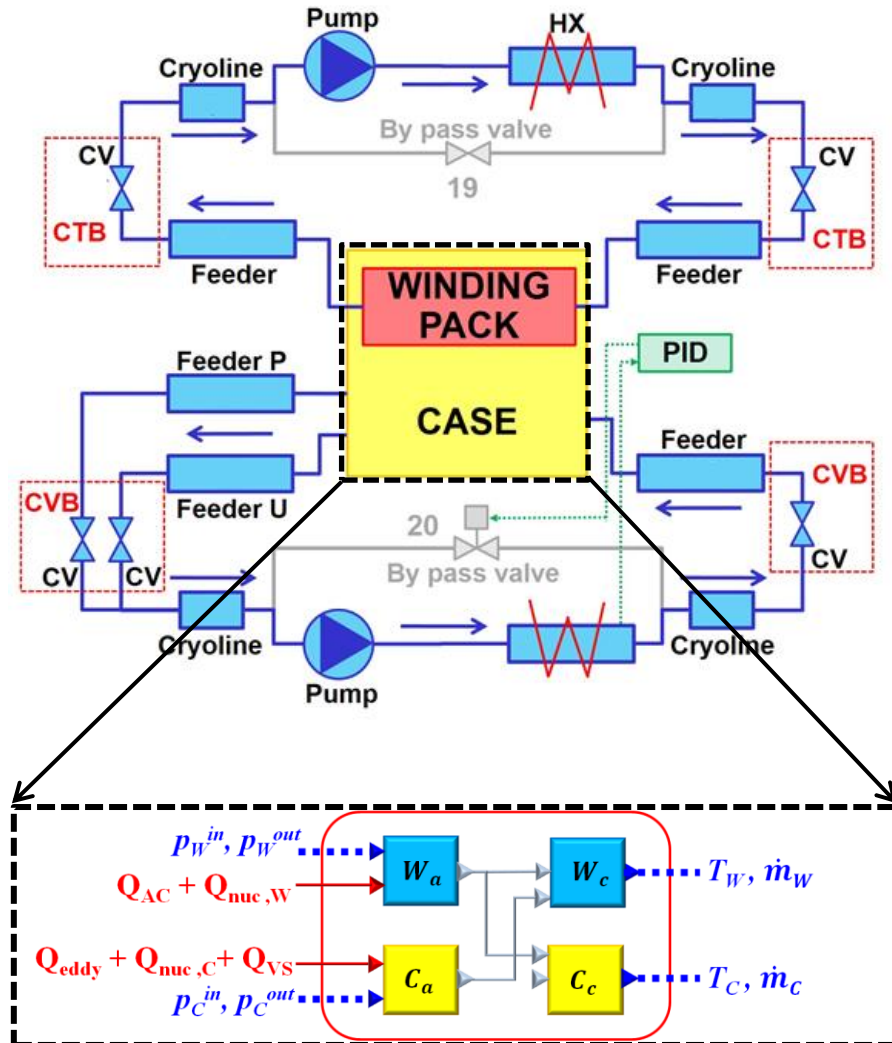


Figure 2. 4C model of the ITER TF cooling loops, with the detail on the ANN model of WP and casing in the inset. The variables transferred from the circuit to the ANNs and viceversa are reported in italic with dashed arrows, while the power inputs to the ANNs are shown with solid thin arrows (details can be found in [16]).

The heat loads to the winding and casing are first given in input to two separate ANNs (one for the winding, W_a , and the other one for the casing, C_a), which have been trained from simulations in which winding and casing were adiabatic (i.e., connected through a perfectly insulating material). These networks receive also in input the inlet and outlet pressure from the 4C circuit model, as shown in the inset of Figure 3. As outputs, these networks compute the inlet and outlet mass flow rates, which are provided directly to the 4C circuit model, and the “adiabatic” He temperature at the coil outlet. In a second stage, two coupling ANNs (W_c and C_c) post-process the “adiabatic” outlet temperatures computed by W_a and C_a , providing the 4C circuit model with the outlet temperatures of the coil WP and casing, and properly accounting for the thermal coupling between the two.

2.1. Training

To train all the networks needed to build the model, the results of several 4C simulations have been used. All the heat loads (nuclear radiation and AC losses in the winding, nuclear radiation, eddy currents and vertical stabilization in the casing) were considered, and applied with a sigmoid waveform with varying amplitude [14], in order to cover the whole range foreseen for plasma operation; the spatial distribution of the heat deposition was the same of the standard operating scenario of ITER [19, 20]. In addition, simulations have been done keeping the heat load at constant level, but varying the mass flow rate through the casing cooling channels, again with a sigmoid waveform, acting on the bypass valve or on the mass flow forced by the circulator. The training range is represented by the grey area in Figure 3, which includes the whole trajectory of the system.

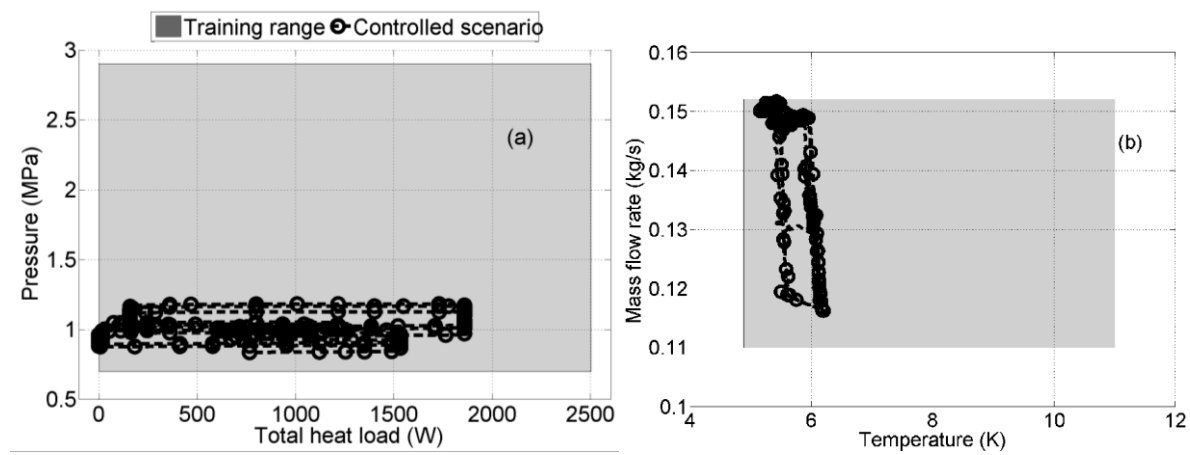


Figure 3. Trajectory in the phase space of the best smoothing scenario: (a) input variables; (b) output variables.

3. Results

3.1. Standard plasma operation (no active control and regulation)

In order to check its validity, the model has been initially tested against the standard operating scenario at 15 MA, with a total nuclear heat load of 14 kW (the waveform of the heat load during the 1800 s of the pulse is reported in [16]), without any action of the control system.

In order to reach periodicity, the pulse is repeated 5 times; the results are shown in Figure 4, compared with the full 4C results in the same conditions [19, 20], in terms of power to the LHe baths of the winding and casing. The accuracy of the ANN model is very good, with a relative error at peak power $\sim 3\%$ for the winding and $\sim 4.2\%$ for the casing (once periodicity has been reached).

Note that the very small loss in accuracy compared to the 4C code corresponds to a huge gain in speed: the ANN model is $\sim 10^3$ times faster than the full 4C model, and it can be much faster than real-time basically independently on the hardware used for the simulation.

3.2. Standard plasma operation (active control and regulation)

3.2.1. Test of heat load smoothing strategies through the ANN model. Since the ANN model has been proven to be very accurate, it can be used in place of the detailed model to evaluate different strategies to smooth the heat load to the cryoplant, allowing e.g. parametric studies to be performed in a very short time.

We concentrate here on the smoothing of the heat load by opening the bypass valve (BVC, see Figure 2) in the casing circuit, which is 100% closed in nominal conditions. The opening of the BVC - the maximum value for the valve opening is set to 20%, leading to a reduction of the mass flow rate

through the coil of ~30% - is controlled with a PI controller, which acts on the basis of the value of the heat exchanged at the LHe bath (evaluated as total enthalpy drop through the heat exchanger). The parameters driving the PI controller action are:

- Set-point (SP): is the value of power that the controller tries to reach and keep constant;
- Proportional gain (K_p): controls how much the controlled variable changes, for a given change in the input; the higher its value, the faster the controller response;
- Integrator time constant (t_i): controls the dependency of the controlled variable on the integral of the error; the contribution of the integral term results in a faster evolution of the process variable towards the set-point, but may cause overshoot. The higher the value of t_i , the smoother the response.

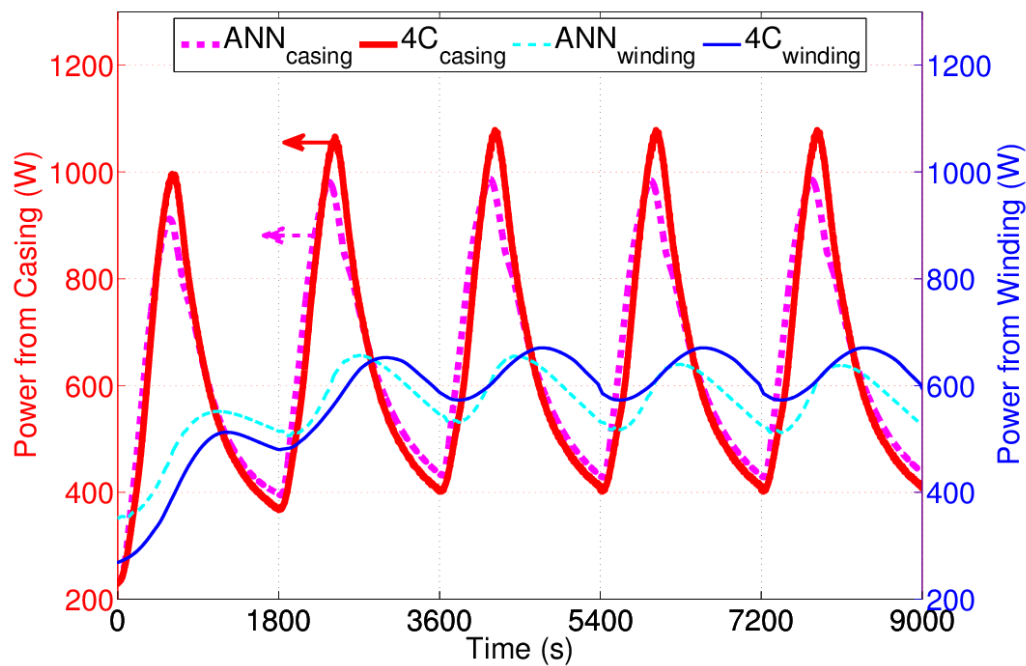


Figure 4. Computed evolution of the power from the winding (right axis, thin lines) and casing (left axis, thick lines) cooling circuits to the respective LHe baths, during a repetitive 15 MA – 14 kW plasma scenario. ANN (dashed lines) and 4C (solid lines) results.

Here a parametric study is performed on each of these control parameters, as summarized in Table 1, to find the most effective smoothing strategy. The results of this study are shown in Figure 5, where only the third pulse is shown, while the chosen values of the parameters are reported in the third column of Table 1.

Table 1. Reference and best values for the parameters of the PI controller.

<i>Parameter</i>	<i>Tested range</i>	<i>Best value</i>
Set-point (SP)	700 W - 940 W	820 W
Proportional gain K_p	5×10^{-4} - 5×10^{-2}	5×10^{-3}
Integrator time constant t_i	100 s ¹	100 s

¹ The parameter t_i has not been tested, as its effect is similar to that of K_p .

In Figure 5a, b the integrator time constant t_i and the proportional gain K_p have been kept equal to 100 s and 5×10^{-3} , and only the SP was changed. It is shown that, the lower SP value (700 W) is too low and cannot be followed with the chosen value for the maximum opening, and so the peak power increases up to ~ 820 W, much higher than the set point. This value is then chosen as SP for a second attempt: also in this case the controller reaches saturation (Figure 5b), but for a time period much shorter, so that the power remains at the set-point level. A final attempt is done considering a high value for the SP (940 W): the controller does not saturate, and the variation of the BPV opening is too small to reach a significant reduction of the heat load peak reduction.

In Figure 5c, d t_i is kept constant (100 s) as well as SP (820 W), while K_p is progressively increased from 5×10^{-4} to 5×10^{-2} : as expected, this has the effect of making the response of the regulated variable progressively faster. In the first case ($K_p = 5 \times 10^{-4}$), the smaller gain has the effect of an averaging filter on the valve opening, allowing a large power increase before the control becomes effective and leaving the valve open when it is not necessary anymore. In the latter case ($K_p = 5 \times 10^{-2}$), the valve responds quickly to small variations in the power, leading to big oscillations during transients. The effect of t_i is not shown here, as it is similar (but reversed with respect) to that of K_p : the higher t_i , the slower the response.

The best smoothing scenario among those considered here corresponds to $SP = 820$ W, $K_p = 5 \times 10^{-4}$. The trajectory of this best scenario is plotted in the phase space of the training, to gain confidence in the computed solution by checking a posteriori that it does not go beyond the limits seen during the training phase, see Figure 3.

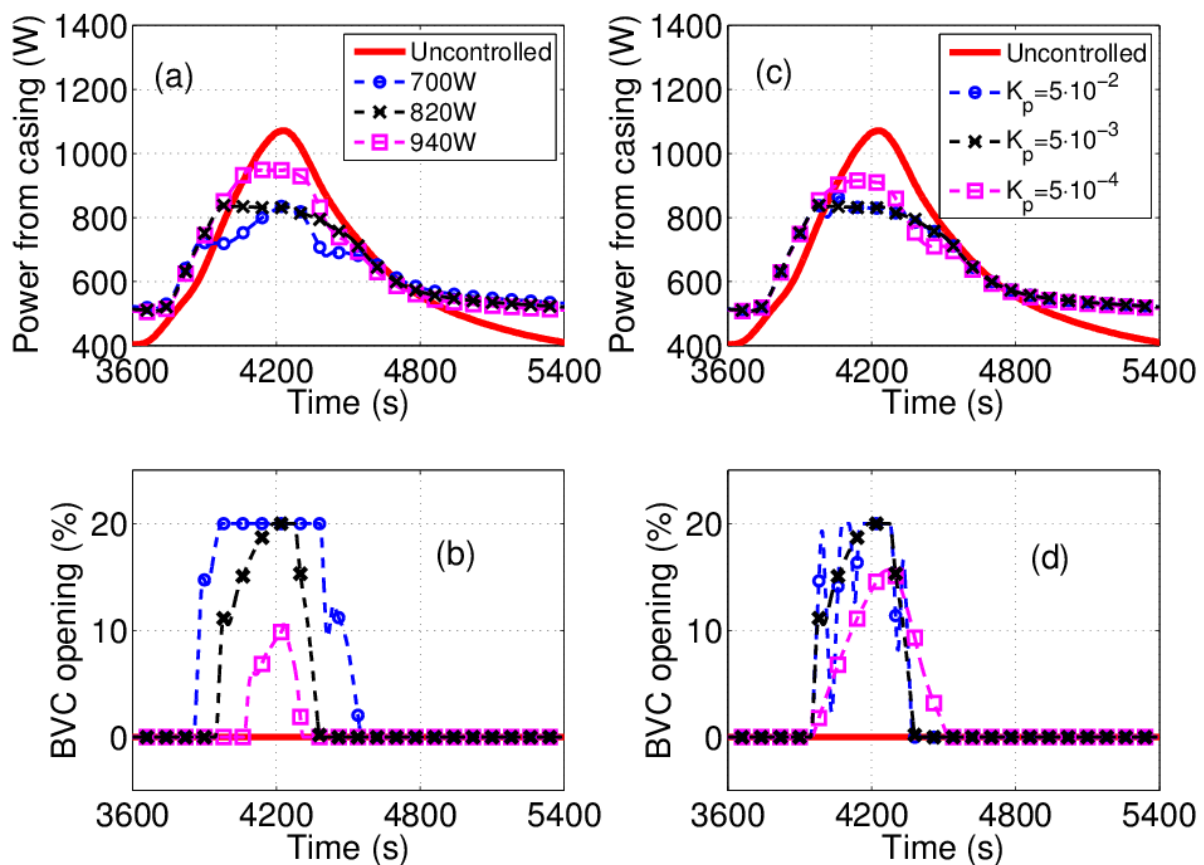


Figure 5. Results of the parametric analysis on the effect of the variation of the set-point (a, b) and effect of the variation of the proportional gain (c, d) in the controller: (a, c) evolution of the power transferred to the LHe bath and (b, d) of the BVC opening. The lines with 'x' markers represent the strategy identified as the best one.

3.2.2. Comparison of ANN and 4C models for the best smoothing scenario. When the best smoothing strategy has been chosen, the computed results are compared with those obtained by the 4C code, in terms of accuracy and computational time. The outcome of the comparison is presented in Figure 6. As already shown in Figure 3, the heat load to the LHe baths computed using the ANN model is again very accurate, with an error on the peak power of $\sim 1.2\%$ in a periodic pulse, but at a computational cost which is reduced ~ 1200 times with respect to the 4C code.

The very high level of accuracy in the computed heat load, together with the gain in speed, allows concluding that the ANN model can be further used to develop and test alternative smoothing scenarios in a reliable way, provided the transient stays inside the training range for the ANN input and output variables.

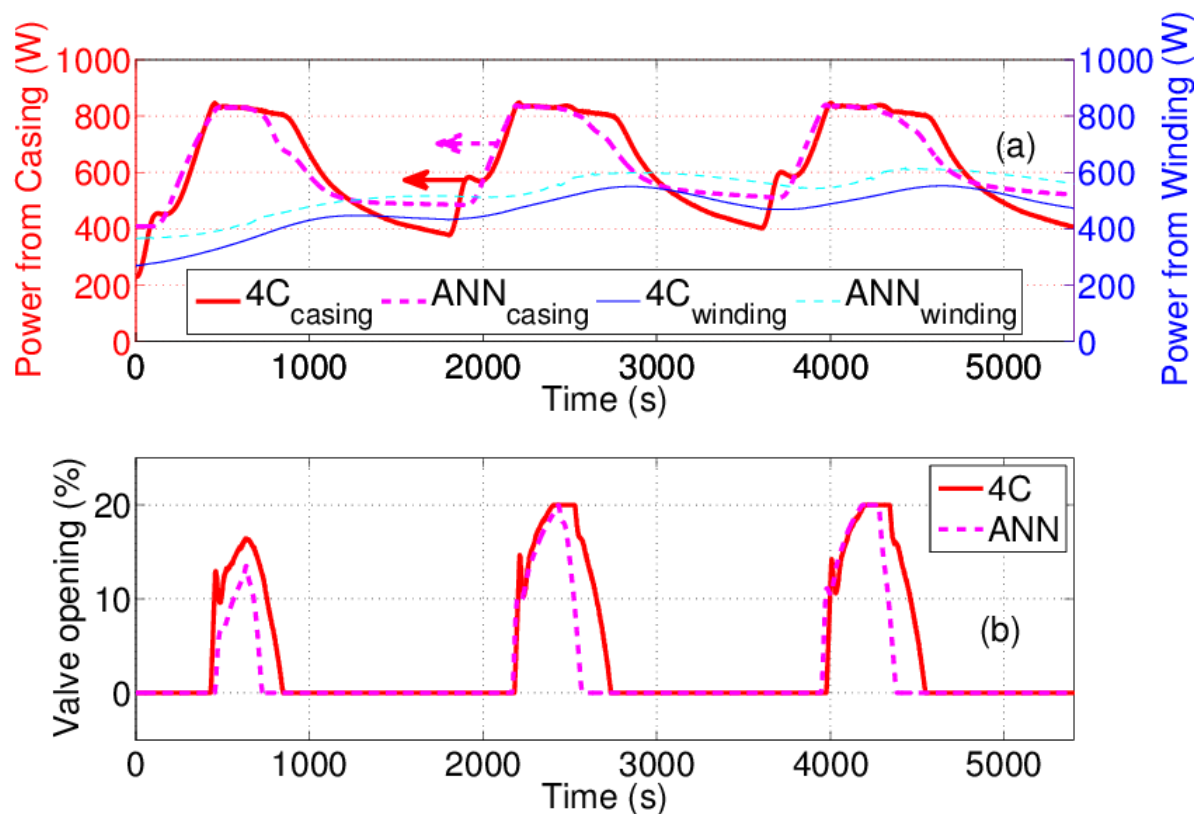


Figure 6. Comparison of the ANN model (dashed lines) and the 4C model (solid lines) for the best smoothed scenario: (a) evolution of power to the LHe bath of the casing cooling circuit (right axis, thin lines) and of the winding (left axis, thick lines); (b) BVC opening.

4. Conclusions and perspective

A simplified model of an ITER TF coil cooling circuits has been developed based on ANNs trained using the results of several 4C code simulations. The ANNs have then been embedded into the 4C model for the cryogenic loops and used as black boxes instead of the 4C detailed model of winding and casing.

This simplified model has been shown to be able to reproduce the results of the full 4C model with a very good accuracy, both when no control is acting on the cryogenic loop and when the bypass valve in the casing cooling loop is regulated by means of a PI controller. The model has been demonstratively used here to optimize the combination of parameters characterizing the PI controller, aimed at achieving the best smoothing among the different tested options, in terms of capability to keep the heat load at the set-point level.

The ANN-based model turns out to be $\sim 10^3$ times faster than that based on the full 4C code, and, as such, fully compatible with real-time operation. It is therefore a viable tool for the design and optimization of control strategies, provided the system trajectory remains inside the parameter range of the training.

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