DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK FOR PREDICTING SPATIAL INTERDEPENDENCIES OF REACTIVITY EFFECTS IN SODIUM FAST REACTORS

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Abstract

Artificial Neural Networks (ANN) are presented as a very powerful tool for modelling complex systems. This approach is becoming increasingly widespread and it has a great potential for nuclear reactor applications. In this work, an ANN is developed for predicting sodium void effects in a large Sodium Fast Reactor core and their spatial interrelations. The ultimate goal is to provide more realistic inputs to the thermal-hydraulics code TRACE for point-kinetics-based transient analysis of the most recent ESFR core conception. With that goal, an ANN is developed and trained to provide the global sodium density effect, receiving as input the normalized sodium density at the different regions of the core. Local reactivity effects are computed using ERANOS deterministic code for an extensive set of combined scenarios in order to train the ANN. The developed model can predict the reactivity evolution taking into account the spatial interrelations between active core and sodium plenum.

1. INTRODUCTION

Sodium-cooled Fast Reactors (SFR) have been identified as the most promising technology among the Generation-IV nuclear reactors. With the aim of further improving the safety level of the commercial-size European Sodium Fast Reactor (ESFR), the Horizon 2020 ESFR-SMART project (European Sodium Fast Reactor – Safety Measures Assessment and Research Tools) was launched in September 2017 [1]. The project is not only devoted to the re-design of the ESFR, which was previously developed in the frame of the CP-ESFR project [2], but also to the development of methodologies in supporting safety assessments.

The safety level of SFR is directly related with reactivity feedbacks and, specifically, the sodium void reactivity. One of the most challenging design aspects is to minimize the sodium void reactivity in the system since it is positive in the fuel regions due to the neutron spectrum hardening when sodium density decreases. Then, the low-void reactor concept is usually proposed as an improvement by means of the introduction of a sodium plenum above the active part of the core. Thus, neutron leakage plays an important role in case of sodium-voiding transient leading to an overall reduced reactivity effect. The ESFR-SMART core design implements this measure and a sodium plenum is introduced above the fuel region and topper by an absorber material layer [3].

Safety analyses under transient conditions rely on point-kinetics-based transient codes. In general, these codes receive as input maps with the spatial distribution of reactivity feedbacks which are precalculated using a neutron transport code by a direct perturbation approach. Nevertheless, this methodology may neglect the effect of the strong spatial correlation between the upper active core part the sodium plenum as well as additivity effects. Neglecting those correlations in the sodium void worth map and consequently in the transient analysis may lead to unrealistic transient results [4]. For the ESFR-SMART core, a detailed study about the spatial interdependencies of main reactivity effects has been carried out by Krepel et al. [5]. Among the main findings of that work, strong non-additive and non-linear effects are found for the sodium void coefficient in the upper fuel part and sodium plenum. That is, the top fuel zone is strongly influenced by the sodium plenum and vice versa in terms of sodium void worth. Then, the sum of both individual contributions does not correspond to the global effect when both zones are voided at the same time. Consequently, accounting for the spatial correlations appears to be mandatory for an appropriate quantification of the overall sodium density-related effect. In this regard, previous efforts were focused on the characterization of these interrelations and the same conclusions were presented [6].

As next step, a methodology can be proposed for providing realistic safety related coefficients to a thermal-hydraulic system code. Artificial Neural Networks (ANN) are becoming increasingly widespread and they have a great potential for reactor physics applications. In fact, ANNs are being currently used for many applications in the field of reactor physics as surrogate models that are capable to perform calculations with lower computational requirements [7,8]. Several works have been carried out in applying ANNs as surrogate models for estimating reactor physics parameters such as power peaking factors [9] and also for uncertainty quantification [10].

In this work, an ANN is developed and trained to provide the global sodium density effect, receiving as input the normalized sodium density at different regions of the core. The goal is then to provide more realistic inputs to point-kinetics-based transient codes. With that goal, a comprehensive set of cases are computed in order to capture both the spatial interrelations and non-linear effects observed for sodium void worth. This set of cases is then used for training the ANN leading to a surrogate model that will be applicable coupled with a transient code.

Core discretization is presented in Section 2. Methodology is described in Section 3, dealing with both data acquisition and ANN main characteristics. Results are then presented in Section 4 and main conclusions and future work are summarized in Section 5.

2. ESFR-SMART CORE DISCRETIZATION

The most recent ESFR core design has been proposed within the ESFR-SMART project [11] and, in this work, the core at the equilibrium End of Cycle (EOC) state is selected [12] since it will be subsequently the reference model for transient analyses. The core, whose thermal power output is 3600 MWth, consists of two main active regions, the inner and the outer core, with 216 and 288 hexagonal sub-assemblies respectively. Nonetheless, following the work carried out by [5], the core discretization in the radial direction is based on cooling groups (CG1-CG5) as shown in FIG. 1. In this map, the inner core is not sub-divided and CG1 corresponds completely to the inner core region. On the other hand, the outer core is divided into four CG (CG2-CG5). Models developed for transient codes within the ESFR-SMART project rely on this radial core discretization.

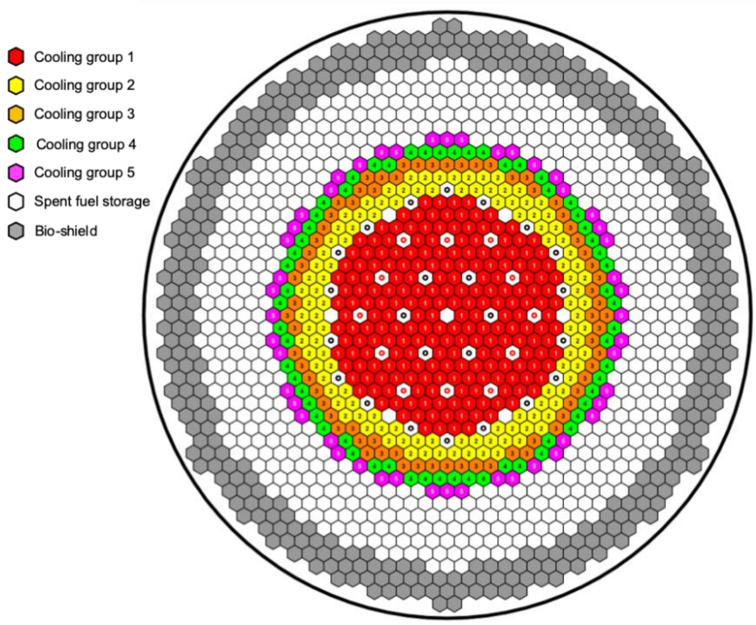

FIG. 1. ESFR-SMART core: radial cooling group distribution.

Concerning the axial description of the core, the main difference between inner and outer core regions is the height of the fissile regions, related to the improvement of the radial power uniformity. In this work, the active core is discretized into 4 axial nodes (Z1-Z4) applying both to inner and outer core regions as depicted in FIG. 2. In the outer part of the core, labelled as Z1o to Z5o, the lower node consists of outer blanket and outer bottom fuel part.

Additionally, as demonstrated in [5], the role of the inner core sodium plenum is greatly important. Then, a more detailed discretization is selected in this case by dividing that zone into three axial slices as shown in FIG. 2. This allows to capture non-additive effects and to characterize the interaction with the upper fuel part (Z4) in detail.

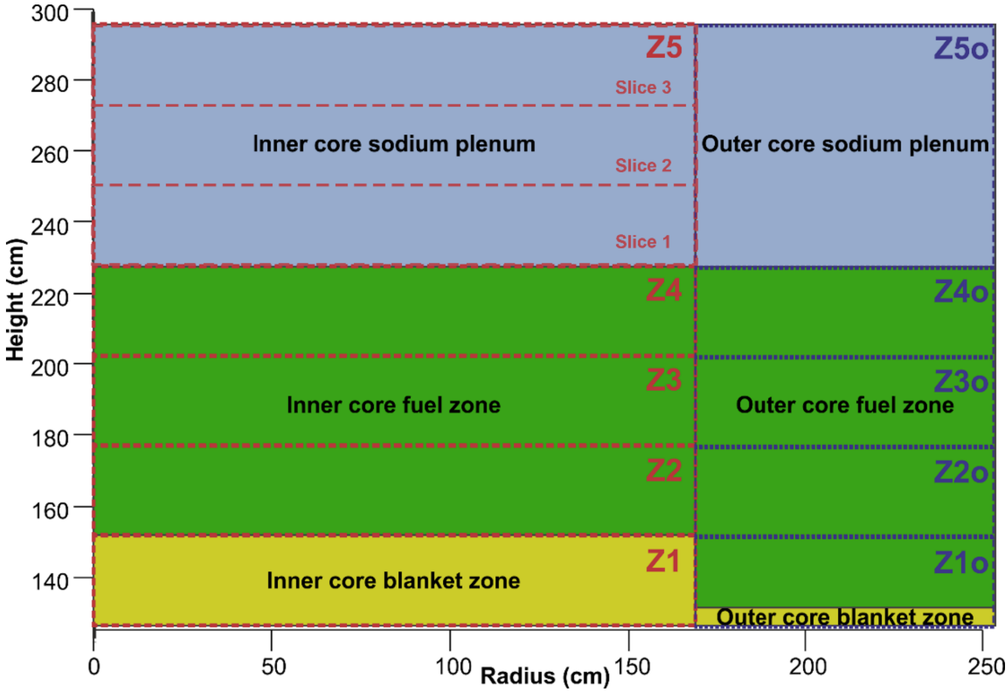

FIG. 2. ESFR-SMART core: axial discretization (taken from [5]).

Then, the model proposed in this work relies on 27 nodes (20 nodes describing the active core along the 5 CGs and 7 nodes representing the sodium plenum) and the dataset should account for all the axial and radial interactions taking place in the core for the sodium void effect.

3. METHODOLOGY

A comprehensive set of cases is generated using the ERANOS 2 code [13] following the methodology described in [5]. In this Section, a detailed description about data generation is presented along with ANN main features and parameters.

3.1. Data acquisition

The database for the training of the ANN is generated by running ERANOS 2 code in a large set of scenarios as a result of multiple spatial combinations. Firstly, each zone is independently characterized as summarized in Table 1. This map can be directly provided to a system code but its application neglects the strong spatial correlations between the upper active core and sodium plenum. Table 2 shows the correlation between the upper core node (Z4) and sodium plenum (Z5) located at CG1 (i.e., inner zone). As it can be seen, the plenum void worth is up to 14% stronger when the upper core is voided while the upper core void worth is 32% lower if the plenum is voided. As verified by [5], this is the strongest mutual interrelation found in the core.

Then, when a traditional sodium void worth mapping is provided to a transient code, spatial correlations are being neglected. Thus, it appears to be mandatory to provide more realistic mapping so that a surrogate model is created by means of the following set of cases:

- 32 cases for every cooling group (CG1-CG5) covering all the axial interrelations as detailed in [5];
- 32 cases combining the main radial cooling groups, CG1 and CG2;

- 35 cases combining all the radial cooling groups for obtaining global values such as full core, whole plenum or whole active core voiding;
- Additional dataset for capturing non-linearities of the sodium void worth in the sodium plenum and its dependency on the upper core part. This is especially relevant as it can be seen in FIG. 3, where non-linearities are clearly observable. Partial void values are also included for those sub-regions that describe the sodium plenum of the CG1.

TABLE 1. Local sodium void worth values calculated by ERANOS (pcm).

Axial node	**CG1**	**CG2**	**CG3**	**CG4**	**CG5**
Z1	7.43	21.55	8.37	-0.63	-1.76
Z2	266.02	164.15	69.92	20.86	-0.01
Z3	470.62	194.33	77.82	23.58	0.61
Z4	137.86	45.45	15.92	2.69	-1.54
Z5	-669.36	-328.17	-160.31	-96.82	-50.18

TABLE 2. Sodium void worth (pcm) at the upper active core node and sodium plenum for CG1, illustrating the correlation between both regions.

Reactivity (pcm)	**Upper core nominal**	**Upper core voided**	**Upper core void worth**
Plenum nominal	794.70	932.55	137.86
Plenum voided	125.33	169.58	44.25
Plenum void worth	-669.36	-762.97	

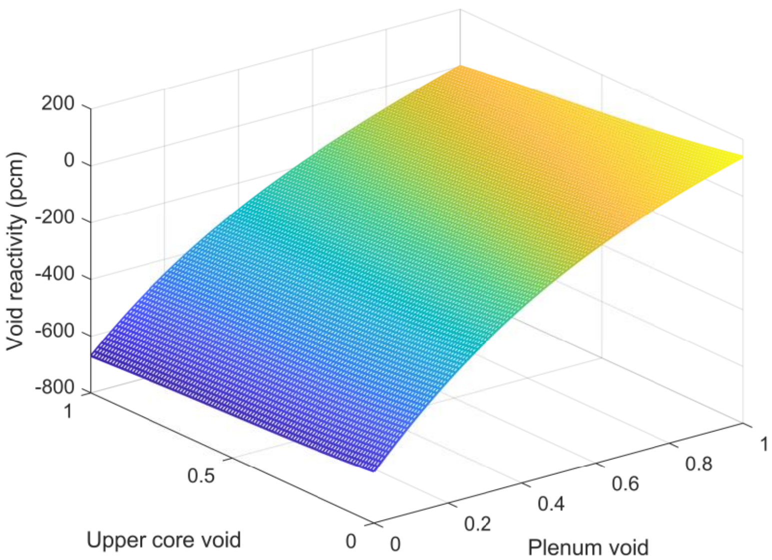

FIG. 3. Mutual interrelation of void effect in upper fuel part Z4 and sodium plenum Z5 (0 – full void, 1 – flooded).

In summary, a dataset of 329 scenarios is prepared accounting for all the relevant spatial interactions of the sodium void coefficient along with non-linearities of the sodium plenum corresponding to CG1, which is the most compromising region.

3.2. Artificial Neural Network

Feedforward neural networks with fully-connected layers is the fundamental deep learning model [14]. Deep neural networks (DNN) are based on a simple structure, where input and output layers are connected via hidden layers that consist of a set of neurons trained using the information provided by the user. At the end, an ANN works as surrogate model for which the user provides the input vector and obtains the ANN final response. In this work, the ANN is programmed under Neural Networks toolbox of the MATrix LABoratory (MATLAB) [15].

A DNN is constructed aiming to predict a single parameter, the global sodium void coefficient, based on a input vector of 27 locations, each corresponding to normalized sodium density at every core region. Then, input parameters are varying between 0 (full void) and 1 (flooded).

Several parameters describe the structure of the ANN and its performance is directly related to the hyperparameters training. From the architectural point of view, the user has to define both the number of hidden layers and the number of neurons per layer. On the other hand, each neuron has an assigned weight that is updated during the training phase in order to minimize the selected cost function (e.g. Mean Absolute Error or Mean Squared Error). Neurons' weight is then corrected during the backward iteration process for which each step is called epoch. A transfer or activation function is applied between layers and for regression models the so-called ReLU (rectified linear unit) activation function is recommended [10] but other functions can be considered.

A simplified architecture is considered in this work since a feed-forward ANN is employed. The designed ANN contains a fully connected hidden layer with 50 neurons. Mean Squared Error (MSE), defined as the average squared difference between ANN outputs and targets, is selected as cost function so that the ANN is optimized based on the minimization of the MSE. The ANN is trained using the Bayesian regularization back-propagation algorithm which updates neurons' weights during the training.

At first step, the ANN is evaluated using the existing dataset by comparing its outputs with the desired target (see FIG. 4) showing a proper behaviour. A maximum error of 15 pcm is obtained showing an adequate behavior. The developed model should be able to predict the sodium void coefficient from the nominal case to the full voided scenario just receiving the normalized sodium density at each slice. Then, a detailed analysis of the ANN performance in presented in the following section.

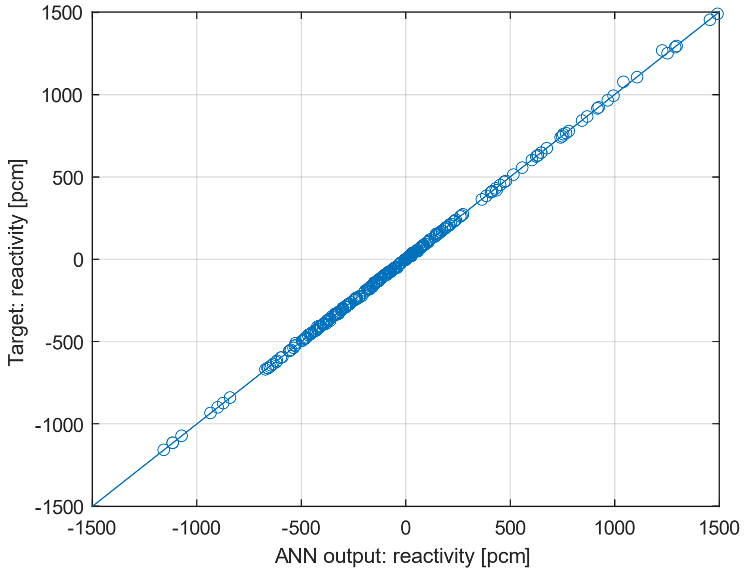

FIG. 4. Regression values of the ANN.

4. RESULTS AND DISCUSSION

In this Section, the surrogate model is in-depth analysed with the aim of proving that, given an input configuration, it provides a reasonable sodium void reactivity variation. The ANN has been trained with discrete values but it is applied for the entire range where sodium density can oscillate, even when sodium density increases. With that goal, FIG. 5-9 show the predicted sodium density reactivity variation depending on the sodium density evolution. It can be seen that the ANN is able to properly predict reactivity effect for the whole range of sodium densities. It is worth highlighting results obtained for sodium plenum at every cooling group (see FIG. 9).

Sodium plenum corresponding to CG1 (i.e. inner core) is perfectly characterized and the ANN is capturing non-linearities, which are relevant for those transients on which sodium boiling occurs. For the rest of regions, the behaviour is practically linear but non-linearities can be also expected in these cases. Nonetheless, linear dependency is acceptable for fuel regions so the ANN is properly characterizing these zones.

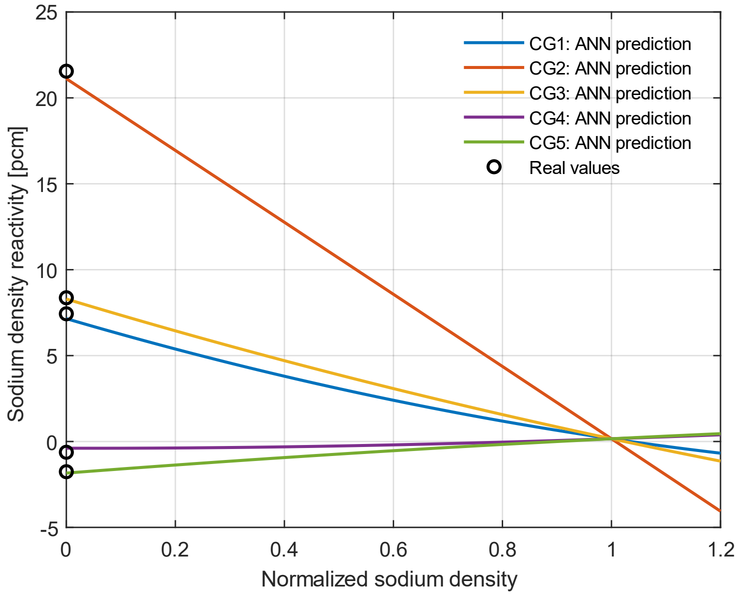

FIG. 5. Sodium density reactivity effect predicted by the ANN for the lower axial node (Z1) at every cooling group along with real values used during the training phase.

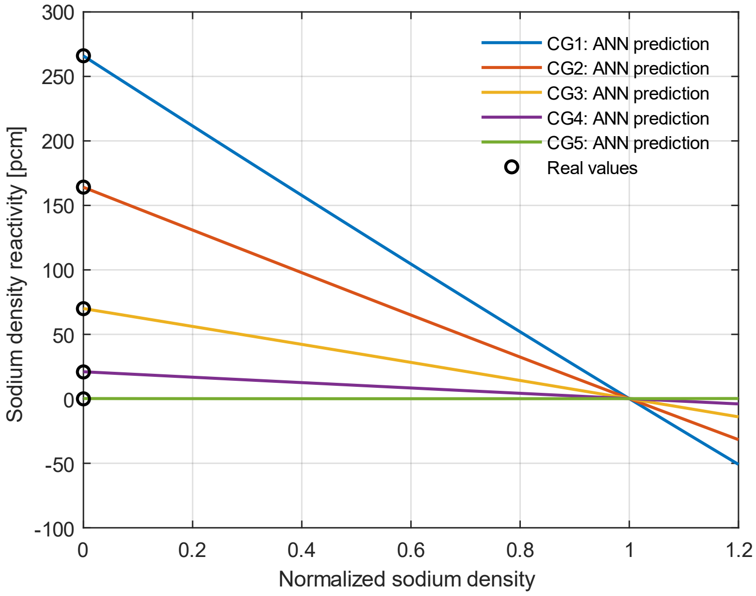

FIG. 6. Sodium density reactivity effect predicted by the ANN for the axial node (Z2) at every cooling group along with real values used during the training phase.

Another relevant effect is related to axial additivity of sodium void coefficient. This effect is studied in FIG. 10, where the axial discretization of sodium plenum corresponding to CG1 allows to verify if the ANN is capturing additivities. The additivity can be easily checked by summation of partial values. For fuel regions, sodium void effect is well additive as demonstrated by [5]. Nevertheless, the additivity assumption is not appropriate for the void effect when the sodium plenum is involved. As it can be seen in FIG. 10, the summation of partial values for each plenum slice does not correspond to the actual whole plenum behaviour. Sodium void effect is stronger when working with the plenum as a whole. As a result, the zone-wise sum is not providing realistic values although it is conservative since provides a higher sodium void coefficient. The ANN also includes this information and it is capable to capture this effect, providing more realistic values when sodium density is changing in the entire plenum.

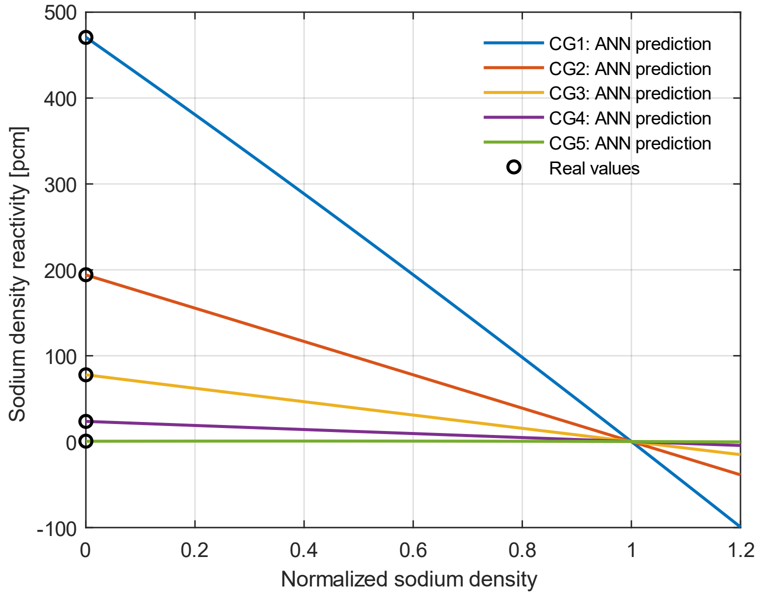

FIG. 7. Sodium density reactivity effect predicted by the ANN for the axial node Z3 at every cooling group along with real values used during the training phase.

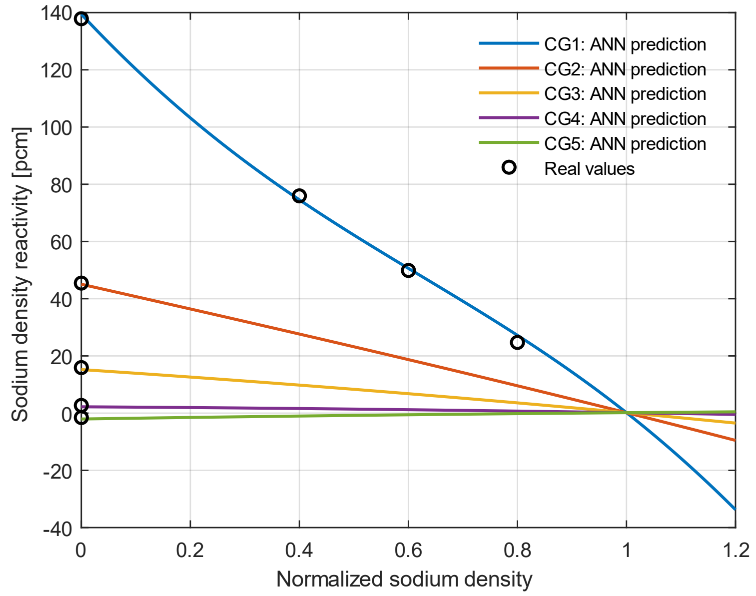

FIG. 8. Sodium density reactivity effect predicted by the ANN for the upper axial node in the active core (Z4) at every cooling group along with real values used during the training phase.

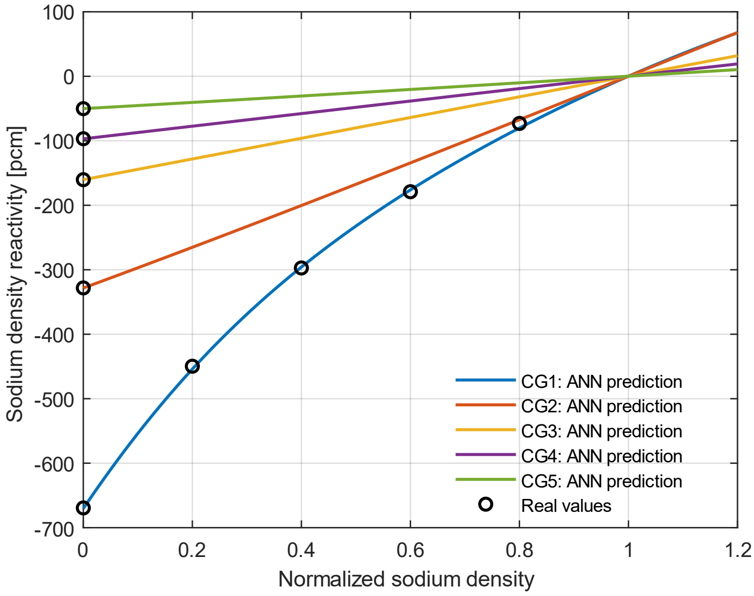

FIG. 9. Sodium density reactivity effect predicted by the ANN for the plenum (Z5)at every cooling group along with real values used during the training phase.

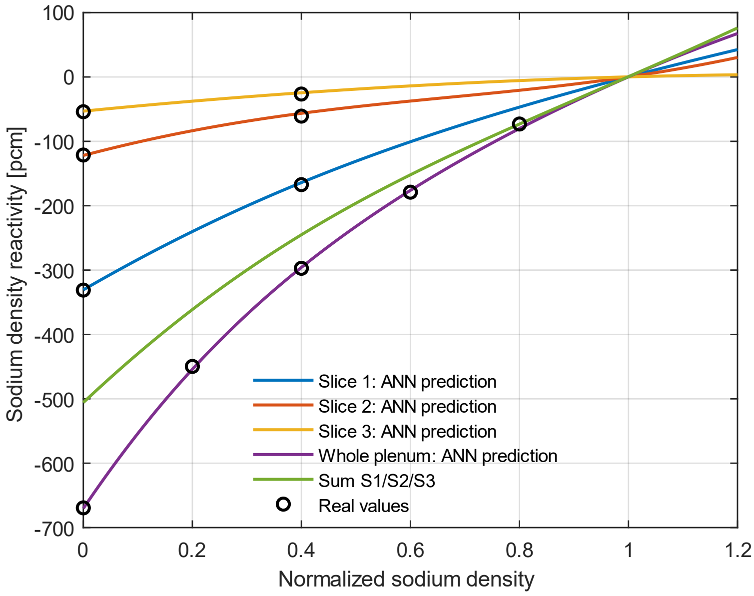

FIG. 10. Sodium density reactivity effect predicted by the ANN for the different slices located in the CG1 plenum.

5. CONCLUSION AND FUTURE WORK

In this paper, a detailed study regarding the sodium void effect is carried out for the ESFR-SMART core. It has been identified that sodium void coefficient is strongly correlated in the upper fuel part and the sodium plenum. This leads to inconsistencies when applying conventional reactivity maps in a point-kinetics-based transient codes because some effects are being underestimated. The main goal of this work is to develop a methodology that allows to provide realistic reactivity feedbacks to these codes. Then, a surrogate model is established for predicting sodium void values in a large SFR along with their mutual dependencies and non-linearities. Artificial Neural Networks are selected due to their capability to deal with high complex systems. This model is trained with a comprehensive dataset computed using ERANOS. The ESFR-SMART core is discretized into 27 nodes and more than 300 scenarios are considered for covering all the spatial interactions of interest. The ANN is successfully created based on a very simple architecture which is just the first step towards a more extended methodology.

Mutual interdependencies between sodium void and Doppler effects are also considered relevant and further extensions of the methodology may be focused on including such interactions. Additionally, the ultimate goal is to provide reactivity coefficients to the selected transient code. Then, the ANN should be coupled with that code in order to feed on-the-fly the transient evolution. This extension is especially interesting for those cases on which sodium boiling takes place. In that case, non-linearities in the plenum will be highly relevant along with the spatial interaction of upper fuel part and the plenum.

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