Transient Capabilities of Deep Learning Assisted Code RAST-AI

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1. Introduction

Artificial Intelligence (AI) assisted tools have become a new norm in our life. It is known that modern internet search engines such as Google or Bing benefit from using AI-improved algorithms. Other areas of knowledge readily inherit such novel methods that offer either saving of time or improvement of accuracy, if not both. Nuclear engineering became yet another new area where AI-driven methods found proper applications.

Ebiwonjumi et al. [1] demonstrated an example of applying Deep Learning (DL), a subset of AI, to improving the accuracy of decay heat calculations in reactor simulations. Shriver et al. [2] applied a Convolutional Neural Network (CNN) to generating pin powers within a 2-dimensional (2D) reflective Fuel Assembly (FA). Dzianisau et al. [3] developed a CNN model later used in a hybrid DL/nodal diffusion code RAST-AI. That model was able to generate 2-group macroscopic cross-sections, pin powers, and assembly discontinuity factors for a FA with variable fuel pin arrangement and a wide range of operational parameters. Further development of RAST-AI included adding Gadolinia (Gd) fuel support into the CNN model [4].

In this study, the capabilities of RAST-AI are extended to modeling not only steady-state problems but also time-dependent problems. The CNN model was trained to generate cross-sections and other parameters of interest for FAs with and without control rods. It also produced kinetic parameters such as decay constants of delayed neutron precursors and their respective yields from fission events. The scope of this paper is to present the testing results of the RAST-AI performance against its very apparent reference, which is our in-house 2-step code system STREAM/RAST-K [5].

The remaining content of this paper consists of 3 sections arranged in the following order. Section 2 contains the description of the reactor model used in our study. In Section 3, the results of three simulation scenarios are presented and compared against the reference code system. Lastly, in Section 4, the primary outcomes and conclusions of the study are restated and summarized.

2. Description of the test model

A large commercially operated Pressurized Water Reactor (PWR) was chosen to test the transient modeling capabilities of RAST-AI. The test configuration was based on a rectangular PWR reactor geometry [6], as shown in Fig. 1. The control rod pattern is given in Fig. 2.

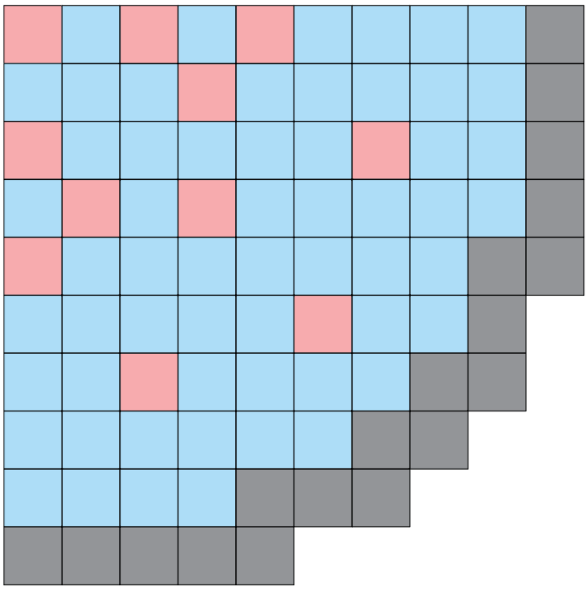

Fig. 1. Loading pattern configuration of the test PWR.

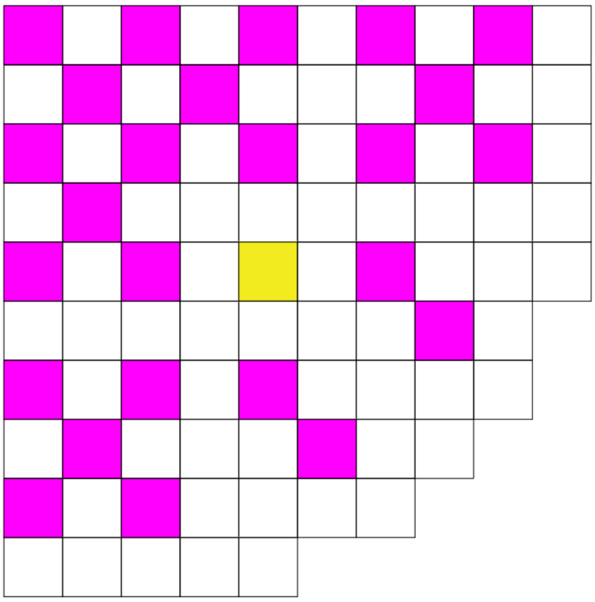

Fig. 2. Control rod configuration of the test PWR.

Each Loading Pattern (LP) used several fresh uranium dioxide (UO_2) FAs (blue) and fresh Gd FAs (red). The core modeling was performed using a quarter-core model with reflective west and north boundaries and vacuum east and south boundaries. The core was surrounded by a steel-water reflector (grey).

Control rods are shown as pink and yellow boxes, and their initial positions are specified for each testing scenario in Section 3. The RAST-AI model was trained with 4-finger B_4C control rods, which is the type of rods used in the test model.

The tested PWR uses a 16x16 FA design adopted in this study since RAST-AI simultaneously supports both 16x16 and 17x17 FA types. One hundred test FA configurations for each of the fuel types were randomly prepared in such a way that fuel pins within the FAs were using 1%, 2%, 3%, 4%, and 5% ^{235}U enrichment, while the Gd pins were using 4%, 7%, 10%, 13% of Gd content mixed with natural UO_2. The Gd pins were specifically designed to have different values of Gd content from the training samples discussed in [4]. It was verified that the test samples do not have the same FA layouts or target Thermal Hydraulic (TH) parameters as in the training or validation datasets.

3. Results of simulation and comparison

To test the transient performance of RAST-AI, three synthetic benchmarks were developed. The first scenario is an accidental rapid ejection of the "yellow" control rod at Hot Zero Power (HZP). The initial conditions of that scenario included all rods being inserted into the core, and the critical state of the core was maintained via the Critical Boron Concentration (CBC) search at 0.0001% of reactor nominal power. The results of modeling the first scenario are shown in Section 3.1.

The second tested scenario was the same as the first one, but operated at Hot Full Power (HFP), the initial critical state of the reactor was maintained at 100% of reactor power. The corresponding result of the second scenario could be found in Section 3.2.

Lastly, the third tested benchmark scenario aimed to test a longer-lasting transient and started with all control rods out of the core (pink and yellow). Then, it was assumed that all rods fall into the core until reaching the bottom. The drop time was chosen to be 2 seconds. The detailed simulation results for the third scenario are listed in Section 3.3.

All scenarios were compared against the reference STREAM/RAST-K code system [5] using identical TH settings and other core-wise settings, as well as identical LP and control rod patterns. Hence, the testing results display the performance of RAST-AI as an alternative to the traditional 2-step code system.

3.1. Hot zero power control rod ejection

The first scenario aimed to test the accident scenario that could happen before the reactor startup. The behavior of the main core parameters, such as excess reactivity, core power, and maximum centerline temperature, is shown in Fig. 3. The red line shows the reference result, and the blue line shows the RAST-AI result. The lines were averaged across all 100 tested LPs; hence, they display the average expected performance from RAST-AI compared to the reference code system.

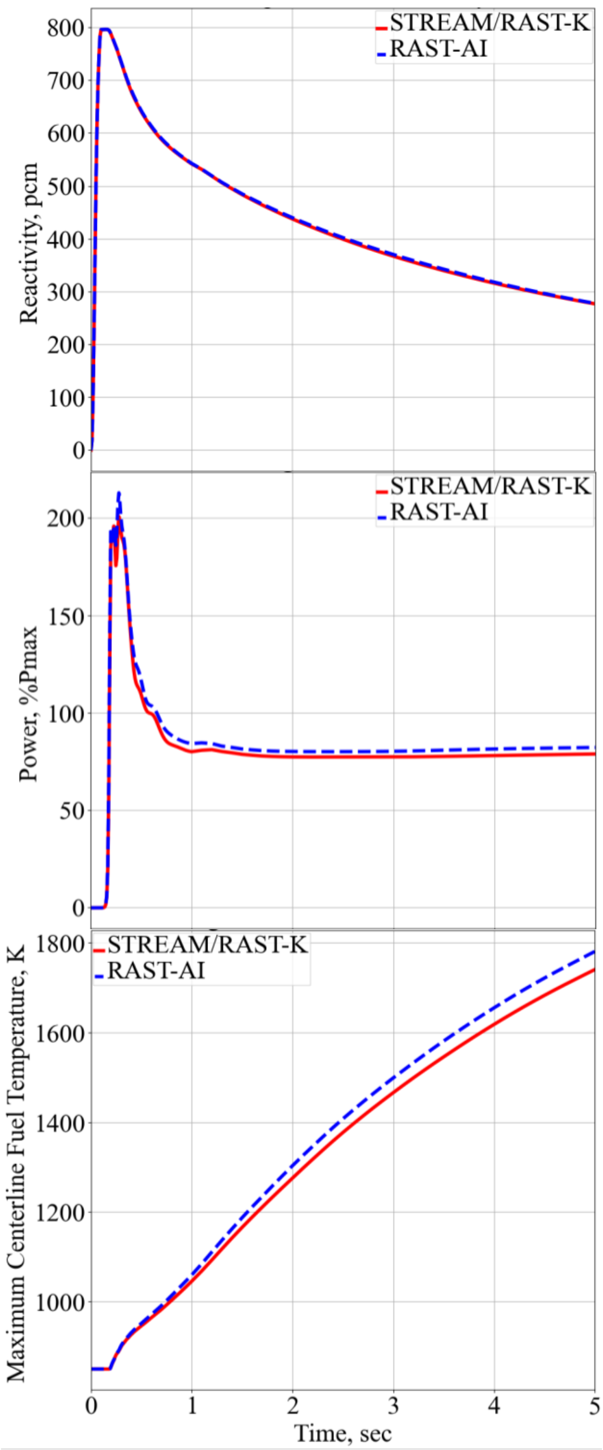

Fig. 3. Average reactivity (top), power (middle), and maximum centerline fuel temperature (bottom) curve for Transient scenario #1 (HZP Ejection).

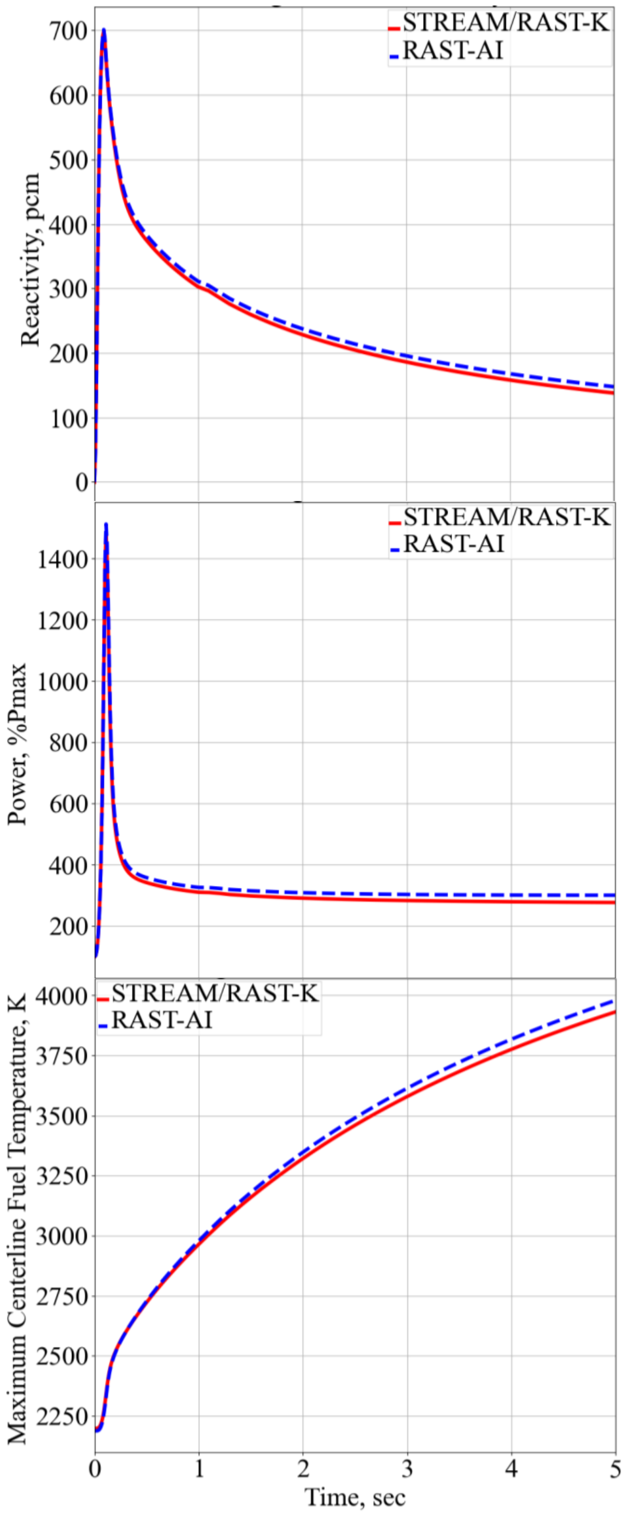

Fig. 4. Average reactivity (top), power (middle), and maximum centerline fuel temperature (bottom) curve for Transient scenario #2 (HFP Ejection).

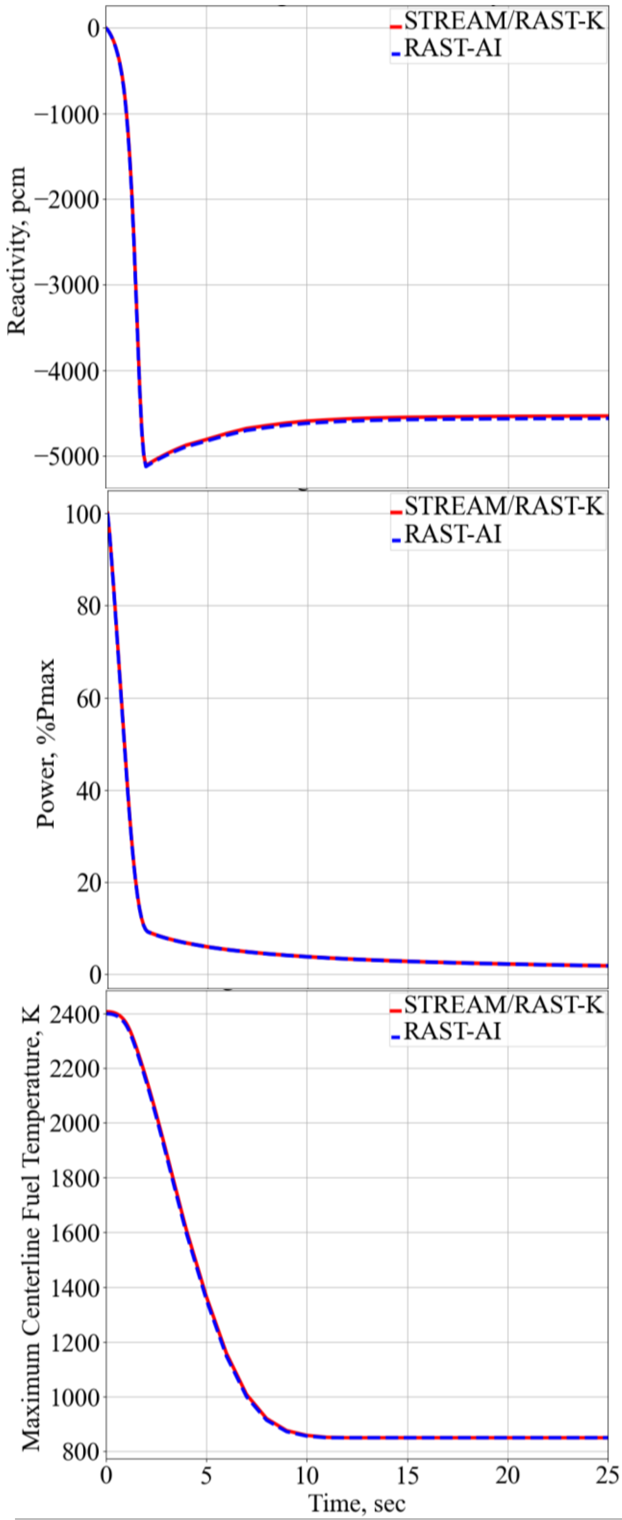

Fig. 5. Average reactivity (top), power (middle), and maximum centerline fuel temperature (bottom) curve for Transient scenario #3 (HFP Trip).

3.2. Hot full power control rod ejection

The second transient scenario was the most artificial among those presented in this paper. The simulation conditions were the following. All control rods were inserted into the reactor core, which was then set to the critical state and Hot Full Power (HFP) using CBC search. At HFP, the yellow rod was rapidly withdrawn from the core, similar to the previous HZP accident scenario. The corresponding transient curves for the main parameters of interest are shown in Fig. 4. Similar to Section 3.1, the main parameters of interest were excess reactivity, core power (in % from the nominal power), and maximum centerline fuel temperature. The RAST-AI result is shown as the blue line, while the reference result stays as the red line.

3.3. Hot full power insertion of all control rods

Lastly, a longer-lasting scenario was modeled and had the following initial conditions. Initially, all control rods were fully ejected, and the core was at HFP and in critical condition via the CBC search. Then, all rods were inserted into the core during the 2-second period. By that, the reactor trip condition was modeled to some extent. The parameters of interest, in this case, stayed the same as before: excess reactivity, core power in % of the nominal power, and maximum centerline fuel temperature. Given the scenario's duration, a more significant impact on the moderator temperature was expected, thus offering a more thorough testing of cross-section feedback.

3.4. Summary of the RAST-AI transient performance

The absolute differences between RAST-AI and STREAM/RAST-K presented in Fig. 3-5 are summarized in the form of Table I.

Table I: Metrics of absolute differences calculated for the tested scenarios.

Metric	Reactivity, pcm	Power, $\%P_{max}$	Centerline Fuel Temperature, K
Scenario #1 – HZP Ejection of the “yellow” rod			
Mean	1.45	4.01	13.21
Maximum	3.10	13.26	40.43
Median	1.47	4.01	8.72
Scenario #2 – HFP Ejection of the “yellow” rod			
Mean	8.08	17.84	15.17
Maximum	9.73	47.75	47.89
Median	8.46	16.57	10.83
Scenario #3 – HFP Trip (rapid insertion of all rods)			
Mean	20.15	0.12	7.63
Maximum	43.91	0.55	12.43
Median	17.64	0.03	9.24

The reasons for choosing each of the given parameters are the following. First, excess reactivity is a valuable metric to observe the core state and is very indicative of the simulating software performance. Second, the core power is a typical parameter of interest and defines various secondary parameters that are not presented in this paper for brevity. Lastly, the maximum centerline fuel temperature was chosen because it could show reaching a fuel melting condition.

The reactivity curve showed decent performance for all tested scenarios. The core power performed worse in absolute values but was reasonably accurate in relative terms, given the range of power change in the corresponding scenarios. Lastly, the fuel centerline temperature was found to be moderately higher in the RAST-AI calculation compared to the reference, indicating additional conservatism in calculations. Overall, the results demonstrate that RAST-AI could be a suitable tool for transient calculations in educational or training projects. It could be used as a preliminary tool for various FA-level optimizations that would take too long if conducted via the conventional 2-step code systems due to the high time burden of generating homogenized cross-sections.

4. Conclusions

RAST-AI is a novel hybrid tool for reactor analysis that utilizes a fast cross-section homogenization DL model and a fast core-wise nodal diffusion solver. The capability to model the reactor behavior in real-time is a crucial option for most reactor simulation codes. In this study, the transient capabilities of RAST-AI were tested using three transient scenarios, 16x16 fresh UO_2 and Gd fuel and B_4C 4-finger control rods. For each scenario, 100 LPs were designed utilizing 100 unique sets of FA layouts for both Gd and non-Gd fuel.

In all tested scenarios, RAST-AI could confidently follow reference solutions produced by STREAM/RAST-K codes. The differences between the codes were found negligible in excess reactivity and more noticeable in some cases of core power and maximum centerline fuel temperature. Overall, RAST-AI showed its potential in solving both steady-state and time-dependent problems, thus becoming a more well-rounded tool for educational or fuel optimization purposes.

Acknowledgment

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REFERENCES

[1] B. Ebiwonjumi, A. Cherezov, S. Dzianisau, D. Lee, “Machine Learning of LWR Spent Nuclear Fuel

Assembly Decay Heat Measurements", Nucl. Eng. Tech., 53(11): 3563-3579, 2021.

[2] F. Shriver, C. Gentry, J. Watson, "Prediction of Neutronics Parameters Within a Two-Dimensional Reflective PWR Assembly Using Deep Learning", Nuclear Science and Engineering, 195:6, 626-647, 2021.

[3] S. Dzianisau, K. Saeju, H. C. Lee, D. Lee, "Development of an Artificial Neural Network Model for Generating Macroscopic Cross-Sections for RAST-AI", Ann. Nucl. Energy, 186:109777, 2023.

[4] S. Dzianisau, D. Lee, "Enhancement of RAST-AI Deep Learning Cross-Section Generation Model by Adding Gadolinia Fuel Support", Transactions of the Korean Nuclear Society Autumn Meeting, Changwon, Korea, October 20-21, 2022.

[5] J. Choe, S. Choi, et al, "Verification and validation of STREAM/RAST-K for PWR analysis", Nucl. Eng. Tech., 51 (2): pp. 356–368, 2019.

[6] T. Nguyen, H. Lee, J. Choe, M. Lemaire, D. Lee, "APR-1400 Whole-core Depletion Analysis with MCS", Proceedings of American Nuclear Society Mathematics & Computation 2019, Oregon USA, August 25-29, 2019.