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Burnup Study of SFRs using Monte Carlo Codes (MCNP & SERPENT) and Deep Neural Networks

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1. Introduction

The Sodium-cooled Fast Reactor (SFR) is a leading Generation IV nuclear reactor [1] design, enhancing sustainability and safety. The use of liquid sodium as a coolant in SFRs offers several advantages over traditional water-cooled reactors, including superior thermo-physical properties and high thermal efficiency. A significant advancement in SFR design is the incorporation of gas heat exchange systems using supercritical carbon dioxide (S-CO2) or nitrogen in a Brayton cycle, which improves thermal efficiency and reduces water-related hazards. Sienicki et al. [2] demonstrated the benefits of the S-CO2 Brayton cycle for SFRs, highlighting its potential to eliminate sodium-water reactions and reduce space and cost requirements. The non-water cooling systems make SFRs safer for deployment near residential areas, addressing environmental and safety concerns. International collaboration through the Generation IV International Forum (GIF) [1] has driven SFR technology development, promising improvements in fuel efficiency, waste management, and overall reactor performance, positioning SFRs as key to future sustainable energy solutions.

In this study, burnup calculations were conducted using two Monte Carlo codes, MCNP [3] and SERPENT [4], to evaluate the effective multiplication factors, revealing a difference of up to 300 pcm between the codes. To further analyze and understand these discrepancies, detailed interpolation and extrapolation of the effective multiplication factors were carried out using advanced time series deep neural network algorithms. These algorithms provided more precise insights and predictions, enhancing our understanding and accuracy of the calculations.

2. Methods and Results

Two prominent reactor burnup Monte Carlo simulation codes, MCNP and SERPENT, are essential for calculating the depletion of the European Sodium Fast Reactor (ESFR) [5] with minimal modifications. In addition to traditional simulation methods, neural network deep learning algorithms have emerged as powerful tools for analyzing and predicting complex systems within reactor physics.

2.1 ESFR with minimal modifications

The European Sodium Fast Reactor (ESFR) is a prominent project within the Generation IV reactor development efforts, focusing on creating safer, more efficient nuclear reactors. The story of ESFR begins with the Collaborative Project on European Sodium Fast Reactor (CP-ESFR) and evolves into the European Sodium Fast Reactor Safety Measures Assessment and Research Tools (ESFR-SMART) project [6], highlighting continuous improvements in safety and performance.

Initiated in 2009, the CP-ESFR project aimed to develop advanced nuclear reactors capable of efficient fuel use, waste reduction, and safe operation under various conditions. The project aimed to design a pool-type Sodium Fast Reactor (SFR) with a power output of 3600 MWth. Fig. 1 shows cross-sections of the core geometry as drawn by the MCNP and SERPENT codes. This design was intended to leverage the extensive operational experience of previous SFRs, such as the French Phenix and Superphenix reactors, while incorporating modern advancements in reactor technology.

The CP-ESFR project laid the groundwork for the ESFR by establishing the basic design principles and reactor layout. The ESFR was designed to use mixed oxide fuel (U,Pu)O2, known for its high melting point and low swelling properties, making it suitable for high-temperature and long-duration operations typical of fast reactors. The reactor's primary components, including the reactor core, primary pumps, intermediate heat exchangers (IHX), and decay heat removal systems (DHRS), were conceptualized to ensure robust and efficient operation.

Building on the CP-ESFR project's foundation, the ESFR-SMART project was launched in 2017. This project aimed to refine and enhance the ESFR design, focusing particularly on safety measures in light of lessons learned from past reactor operations and recent nuclear incidents such as the Fukushima disaster. The ESFR-SMART project received funding from the

EURATOM Research and Training Programme, which underscores the European Union's commitment to advancing nuclear safety.

Impressed by the evolution of the ESFR from the CP-ESFR to the ESFR-SMART project and the continuous efforts to enhance the safety and performance of Sodium Fast Reactors, it is highly recommended for studying as a Generation IV reactor model with a promising future outlook.

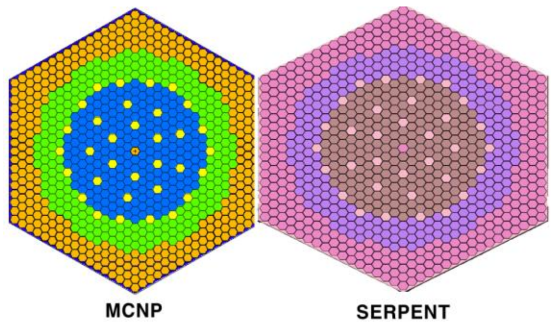

Fig. 1. Cross-sectional views of the core geometry as drawn by the MCNP and SERPENT codes. Inner core fuel assembly, outer core fuel assembly, control and shutdown device, diverse shutdown device, and reflectors are shown.

2.2 Deep learning neural networks

Deep learning neural networks have shown significant potential in time series forecasting, particularly when using rolling windows and regression techniques. These methods offer powerful tools for capturing complex patterns and dependencies in sequential data, which are often challenging to model with traditional approaches.

Time series forecasting [7] involves predicting future values based on previously observed values. Deep neural networks, with their ability to learn hierarchical representations and capture non-linear relationships, are well-suited for this task. The rolling windows technique is a popular method for transforming time series data into a supervised learning problem. This involves creating a series of overlapping sub-sequences from the original time series, which are then used to train the neural network.

Meanwhile, regression analysis in the context of deep learning neural networks [8] involves predicting a continuous output variable based on one or more input variables. By leveraging advanced architectures like Fully Connected Neural Networks, Convolutional Neural Networks, and Recurrent Neural Networks, and employing robust optimization and evaluation methods, deep learning models can achieve high accuracy and reliability in various regression tasks. Continuous advancements in this field promise even greater capabilities for tackling a wide range of real-world problems.

2.3 Keff data (calculated by the MCNP code) forecasting

The relationship between Keff calculation and burnup study is crucial for managing nuclear reactor performance and safety. Accurate keff calculations enable efficient burnup planning, ensuring reactors operate safely and economically. Monte Carlo codes are highly beneficial for Keff calculation, as they simulate particle behavior and interactions precisely, capturing complex geometries and physics. Their versatility and detailed statistical analysis make them essential for criticality safety, reactor design, and operational planning. This interconnected relationship underpins reactor design, operation, and regulation.

Deep learning neural networks were employed to predict Keff values through a rolling windows technique, which transforms time series data into a supervised learning problem. This approach involves creating overlapping sub-sequences from the original time series, which are then used to train the neural network. This method enhances the precision of criticality safety and reactor operation planning by effectively capturing complex temporal patterns. This method leverages the strengths of DNNs in handling complex temporal patterns and can significantly enhance the precision of criticality safety and reactor operation planning. Proper implementation and evaluation can lead to robust and reliable Keff forecasts, supporting the safe and efficient management of nuclear reactors.

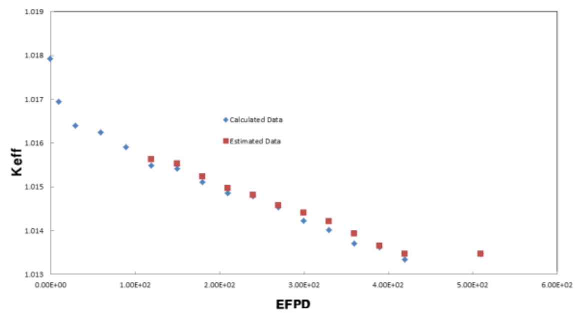

Fig. 2. The effective multiplication factors, Keff, calculated by the MCNP code and estimated by neural networks, as a function of effective full power day (EFPD) for an European Sodium Fast Reactor (ESFR).

Fig. 2 illustrates the application of forecasting Keff for ESFR using the MCNP code. Table I shows forecasted data values that are accurate within one sigma. The predictions of the multiplication factors are claimed to be within one sigma; however, the limited number of data points used in training the neural network poses a challenge to the overall accuracy. The known linear decrease in the Keff by approximately ten pcm per burnup step, with the exception of the initial step, is acknowledged. Despite this, the model’s predictions should be interpreted with caution, and future work will focus on expanding the dataset and refining the model to better capture these stage-specific trends.

It is observed that all predicted values consistently overestimate the actual multiplication factors. This overestimation may stem from the conservative nature of the deep learning model employed, which is likely tuned to avoid under-prediction due to its potential safety implications in reactor operation. Additionally, the model's training process might have been influenced by an inherent bias in the dataset or the loss function used, which penalizes underestimation more heavily.

Table I: Training and forecasting Keff for ESFR

Training Data					Forecasted
Input				Output	
1.01792	1.01640	1.01624	1.01591	1.01548	1.01562
1.01640	1.01624	1.01591	1.01548	1.01541	1.01553
1.01624	1.01591	1.01548	1.01541	1.01511	1.01524
1.01591	1.01548	1.01541	1.01511	1.01485	1.01497
1.01548	1.01541	1.01511	1.01485	1.01478	1.01482
1.01541	1.01511	1.01485	1.01478	1.01453	1.01458
1.01511	1.01485	1.01478	1.01453	1.01422	1.01440
1.01485	1.01478	1.01453	1.01422	1.01401	1.01421
1.01478	1.01453	1.01422	1.01401	1.01371	1.01393
1.01453	1.01422	1.01401	1.01371	1.01362	1.01365
1.01422	1.01401	1.01371	1.01362	1.01334	1.01347
1.01401	1.01371	1.01362	1.01334	X	1.01347

The second predicted value (1.01553) shows an increase compared to the MCNP value from the previous burnup step, which is counterintuitive given the expected trend of gradual reduction. This anomaly may be attributed to the neural network model's sensitivity to slight variations in the input data or the model overfitting to specific data patterns during training. For practical application, it is crucial to refine the model by incorporating more robust cross-validation techniques and possibly augmenting the training dataset to prevent such inconsistencies. Moreover, further tuning and regularization techniques should be explored to ensure that the model adheres closely to the expected physical trends.

2.4 Keff data (calculated by the SERPENT code) regression

Deep neural networks are highly effective in regression tasks, including estimating the Keff for nuclear reactor design. The multiplication factor Keff is a critical parameter in reactor physics that indicates whether a nuclear reactor is subcritical, critical, or supercritical. Fig. 3 shows the Keff values calculated by the SERPENT code and the regression results, which are in good agreement within statistical errors. It is essential to confirm that the same problem was indeed analyzed using both the MCNP and SERPENT codes. The noticeable difference in results between the two codes, particularly the reversal of the expected trend in the second and third burnup steps in the SERPENT analysis, warrants a detailed investigation. This discrepancy could arise from differences in the handling of burnup and neutron transport in the two codes. A thorough review of input files and modeling assumptions is necessary to identify potential causes. Additionally, further validation against experimental data or alternative simulations may be necessary to reconcile these differences and ensure the reliability of the methods employed.

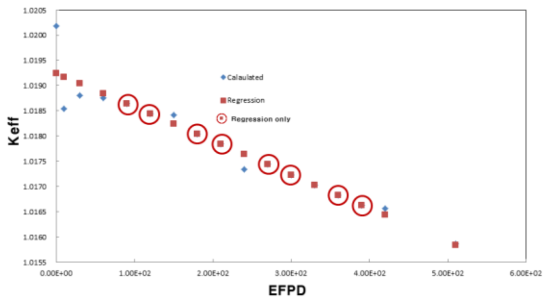

Fig. 3. The effective multiplication factors, Keff, calculated by the SERPENT code and estimated by neural networks, as a function of effective full power day (EFPD) for an European Sodium Fast Reactor (ESFR).

3. Conclusions

This study successfully demonstrated the effectiveness of deep neural networks in predicting the effective multiplication factor Keff for a European Sodium Fast Reactor (ESFR). The MCNP and SERPENT codes provided baseline calculations, revealing slight discrepancies within 300 pcm. Deep neural networks using time series forecasting and regression techniques showed excellent agreement with these calculations within statistical errors. These results confirm the potential of integrating traditional Monte Carlo simulations with advanced neural network algorithms to enhance accuracy and reliability in nuclear reactor burnup studies. The integration of Monte Carlo simulations with deep neural network algorithms demonstrates potential for improving reactor design and safety. However, the study's limitations, such as the small dataset and discrepancies between different codes, highlight the need for further data collection, model refinement, and cross-validation to ensure the method's reliability and practical applicability in nuclear reactor burnup studies.

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