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SMR Computational Analysis Framework Using AI Surrogate Models

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1. Introduction

Small Modular Reactors (SMRs) are attracting attention as a core technology in the next-generation nuclear industry, serving as an essential means for realizing carbon neutrality and establishing distributed energy systems based on their flexible power generation and safety [1, 2]. While high-precision computational analysis codes are essential for SMR design verification and operation simulation, conventional CPU-based thermal-hydraulic system codes face significant limitations. Specifically, time-integration-based system codes easily encounter numerical instability depending on time steps, boundary conditions, and node densities, leading to slow computation speeds. In particular, the steam generator, a core component of the SMR, operates over a wide range of conditions and involves phase changes, thus requiring the most discretization and computational cost during modeling.

To overcome these limitations and accelerate the computational analysis of SMRs, utilizing GPU acceleration technology or applying Artificial Intelligence (AI) surrogate models has emerged as a promising alternative. Recently, various studies have been actively conducted to apply AI in nuclear systems, such as automating plant heat-up modes or autonomous power-increase operations using deep reinforcement learning [3-5]. Building upon these advancements, this study proposes a novel framework capable of real-time or near-real-time computational analysis of SMRs by converging these two approaches. Ultimately, this research aims to replace existing CPU-based computational codes with GPU-based ones to increase calculation speed and further develop a computational analysis platform based on an AI surrogate model with a differentiable structure. The proposed technique dramatically improves computational efficiency, aiming to demonstrate optimal SMR operation scenarios, such as load following.

2. Research Methodology

2.1 Physical Model Construction and GPU Acceleration

The governing equations for mass, momentum, and energy conservation of major thermal-hydraulic components of SMRs, such as the core, pump, and steam generator, are formulated.

A numerical analysis technique based on the Finite Volume Method (FVM) applying a pressure-velocity coupling algorithm is introduced to rigorously simulate the physical behavior of the thermal-hydraulic system.

The established analysis technique will be ported to a GPU environment utilizing Python, CuPy, etc., and a comparison of computational performance and stability with existing CPU computational codes will be conducted.

2.2 AI Surrogate Model Development

Generally, a massive amount of data on the corresponding equipment is required to develop an AI surrogate model. However, at this stage, an AI surrogate model that reconstructs the entire thermal-hydraulic information with minimal measurement information is developed by applying deep learning techniques such as Physics-Informed Neural Networks (PINN).

2.3 Optimal Operation Scenario Demonstration and Control Integration

Once a system code capable of high-speed calculation is established by applying an AI surrogate model, various optimal operation scenarios can be derived. Representatively, diverse operation scenarios, including load increase/decrease and rapid change conditions such as load following, will be selected, and an AI control neural network capable of multivariable control will be trained. This will be compared with conventional control methods to verify the computational stability and accuracy of the coupled system.

3. Implementation Strategy

To achieve the objectives, this study implements the following step-by-step methodology:

- First, we develop an AI surrogate model by introducing physics-based artificial intelligence techniques (PINN).

- Prior to full-system implementation, we develop an AI surrogate model for reactor dynamics. This model is trained using point kinetics equations alone, requiring no pre-existing datasets.
- Subsequently, we perform the development of an optimal power control AI model using the AI surrogate model that simulates the core point kinetics.

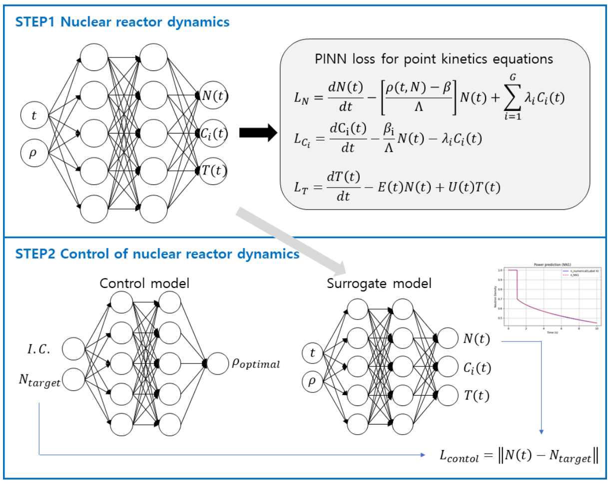

Fig. 1. Core dynamics AI surrogate model and optimal control AI model learning structure.

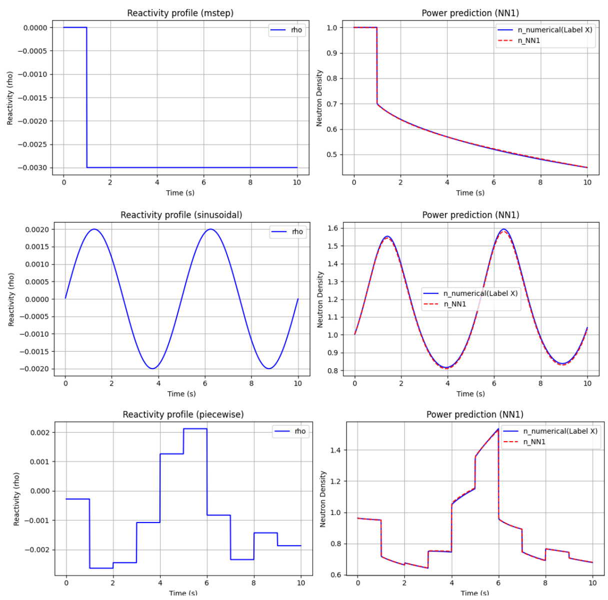

Fig. 2. Implementation of an AI surrogate model for reactor point kinetics equations.

4. Expected Outcomes and Conclusion

This study introduces a novel framework that accelerates SMR system analysis and enables real-time state prediction by combining GPU acceleration and AI surrogate modeling. Beyond merely improving analysis codes, this differentiable analysis platform can serve as a core component for nuclear digital transformation and digital twin technologies. Ultimately, by facilitating the rapid derivation of optimal control paths under various operating conditions, the proposed framework will simultaneously enhance the operational efficiency and safety of SMRs, contributing to the export competitiveness of domestic SMR technology.

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