Development of a Time-Series Surrogate Model for Predicting System Dynamics in KAIST-MMR under Load-following Operation

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Keywords : sCO_2 cooled reactor, load following operation, machine learning, time series surrogate model

1. Introduction

Supercritical carbon dioxide (sCO_2) cycles have garnered significant attention in recent years due to their potential to revolutionize energy conversion processes. These cycles operate at pressures and temperatures above the critical point of CO_2, resulting in higher thermal efficiencies and compact system designs compared to traditional steam cycles. Utilizing the unique properties of sCO_2, KAIST research team have developed the KAIST-MMR (Micro Modular Reactor), utilizing a simple recuperated cycle layout [1].

One of the key advantages of sCO_2-cooled reactors, such as the KAIST-MMR, lies in their ease of control during load-following operation. Since sCO_2 is compressible fluid, the control of reactor power through inventory control of the coolant can be well utilized. Additionally, the single-phase nature of the power conversion system and the simplicity of the layout contribute to the system's suitability for load-following operation. These factors make sCO_2-cooled nuclear systems well-suited for responding to fast varying power demands, offering potential advantages in terms of flexibility and efficiency. Operating under load-following conditions, where power output adjusts to meet varying demands, necessitates a thorough understanding of the system's dynamic behavior. Efficient and precise prediction of system dynamics during load-following operation is crucial for optimizing control strategies to ensure safety and reliability while maximizing efficiency.

Reinforcement learning (RL) has emerged as a promising approach for optimizing control policies in complex dynamic systems. RL algorithms learn through interaction with the environment, making accurate simulation of system dynamics imperative. Hence, the development of a reliable surrogate model capable of accurately capturing the system's transient behavior becomes essential for leveraging RL in the KAIST-MMR system.

In this study, the authors have developed a time-series surrogate model using a combination of convolutional neural networks (CNN) and long short-term memory (LSTM) networks. Leveraging a vast dataset of load-following operation simulations generated by the MARS code, this model aims to accurately emulate the system's dynamic response to different operating conditions. By providing a fast and accurate representation of system dynamics, the proposed surrogate model lays the foundation for efficient RL-based control optimization in the KAIST-MMR system.

2. Methods and Results

2.1 Target system

The target system referenced in this study is the KAIST-MMR. While the original KAIST-MMR employs an air-cooled pre-cooler, where the compressor inlet temperature is set relatively high at 60°C, this research focuses on a modified version, namely the marine type KAIST-MMR. In this variant, the compressor inlet temperature is designed at 35°C following the replacement of the ultimate heat sink from air to water. Figure 1 illustrates the system layout of the target system. Table I presents the design points at various locations within the system, providing key parameters such as pressure, temperature, and mass flow rate.

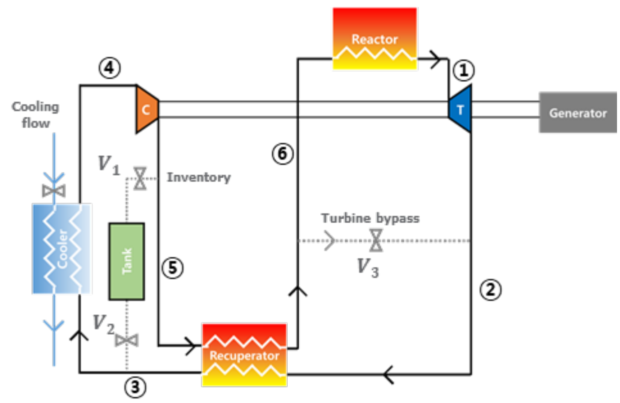

Fig. 1. System layout.

Table I. System design points

Location	Pressure [MPa]	Temperature [°C]	Mass flow rate [kg/s]
1	22.35	550	115.35
2	8.35	437.59	115.35
3	8.1	103.58	115.35
4	8.0	35	115.35
5	22.7	88.73	115.35
6	22.6	340.48	115.35

2.2 Data production

The authors have modified the MARS code, a nuclear thermal-hydraulic analysis tool, to facilitate sCO_2 analysis [2]. Load-following operation data were generated using this modified MARS code. The simulation scenario consisted of a 600-second duration, during which the system underwent various power demand changes. Initially, the system operated at nominal power for 10 seconds, followed by a 180-second period of decreasing power demand. Subsequently, the system operated at reduced output for 120 seconds before returning to nominal power for another 180 seconds, completing the scenario. To introduce variability in ramp rates, the operation at lower power levels (ranging from 60% to 80%) was subdivided into increments of 2%. As a result, ramp rates varied from 6.66% to 13.33%. Figure 2 illustrates the simulation scenario.

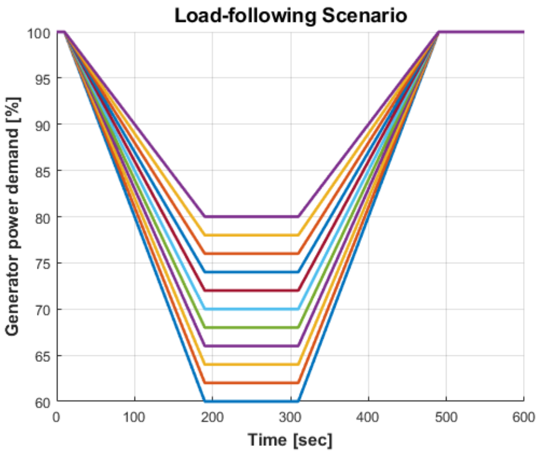

Fig. 2. Various scenarios for load-following operation.

To acquire a wide range of operating data under different scenarios, the PI gain values of the control valves were varied intentionally. Traditional control studies have empirically adjusted PI gains to find optimal combinations. However, due to the complex interplay of multiple valves in the closed-loop power generation system, traditional PID control methods may not be optimal. Hence, Table II demonstrates the division of PI gain settings for each valve to collect a wide range of operating data. The control parameter for all three valves were set to the turbine speed. The control strategy was based on PI control, with the integral gain set at 10% of the proportional gain. The compressor inlet temperature control was considered a single-input/single-output problem due to its independent control by the mass flow rate of the separate cooling water system, thus deemed feasible with PID control alone. Therefore, the surrogate model developed in this study focuses on the effects of three valves: turbine bypass valve (V_1), inventory discharging valve (V_2), and inventory charging valve (V_3), as shown in Figure 1. Real-time optimal control of these three valves will be implemented in future RL experiments. In total, data were generated for 6,393 cases out of 13,310 possible combinations. Each simulation produced 600 seconds of data, resulting in a total of 3,842,193 data points. With 29 variables recorded every second, the input data matrix for supervised learning was 3,842,193 x 29 in size. Figures 3 to 9 present simulation results for several key variables.

Table II. P gain ranges of control valves

Control valve	P gain range	Increment
V1	1-10	1.0
V2	0-0.5	0.05
V3	0-0.1	0.01

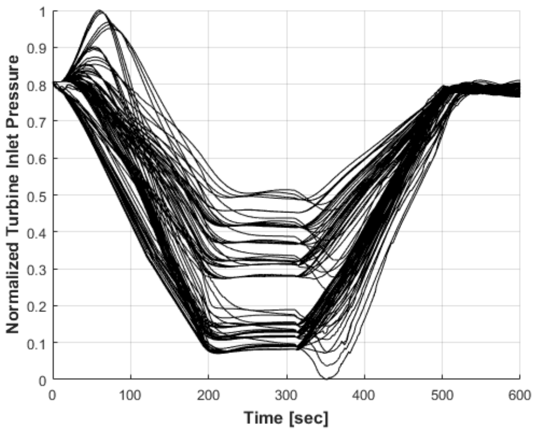

Fig. 3. Normalized turbine inlet pressure.

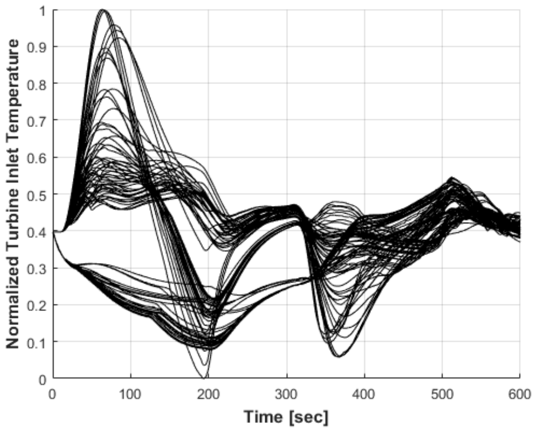

Fig. 4. Normalized turbine inlet temperature.

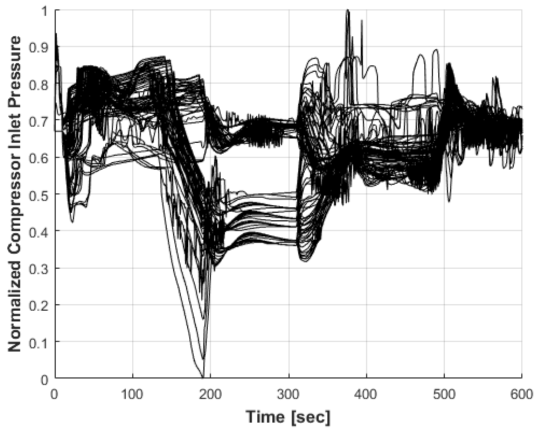

Fig. 5. Normalized compressor inlet pressure.

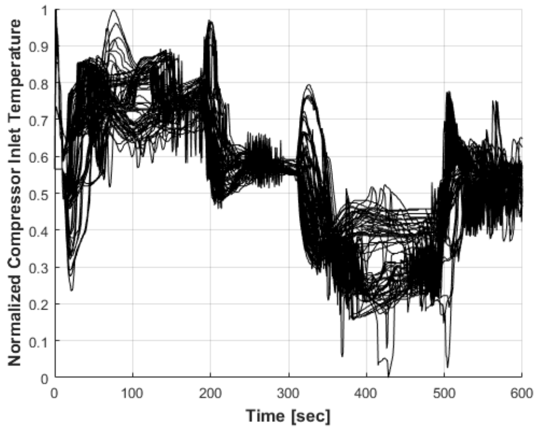

Fig. 6. Normalized compressor inlet temperature.

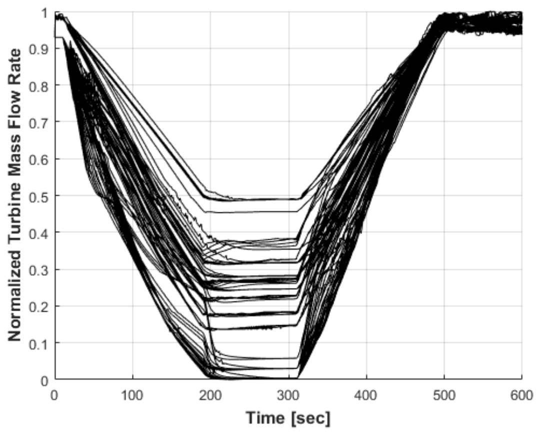

Fig. 7. Normalized turbine mass flow rate.

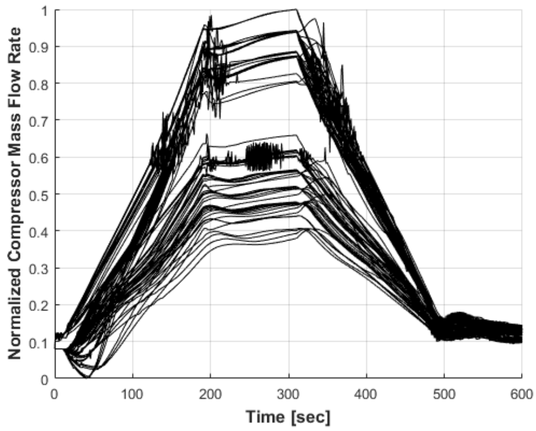

Fig. 8. Normalized compressor mass flow rate.

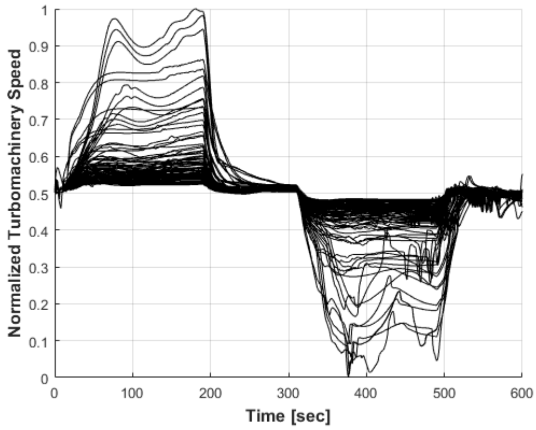

Fig. 9. Normalized turbomachinery rotating speed.

2.3 Time series surrogate model

Predictive models for time-series data have been developed using the rolling window forecast method. The model architecture adopted was a CNN-LSTM structure, depicted in Figure 10. This choice was motivated by previous studies, which demonstrated its superior performance in constructing time-series surrogate models [3, 4]. To forecast the next time step, the model utilized a window size of three, incorporating system information from the preceding three seconds. Illustrated in Figure 1, the model employed 25 system variables and four control variables (generator torque and three control valve stem positions) to predict the system's state at the subsequent time step.

For model evaluation, the dataset was partitioned, allocating 70% for training, 20% for validation, and 10% for testing. Evaluation was conducted using mean absolute error (MAE), as outlined in Equation (1). Performance assessment involved varying the number of neurons in the CNN-LSTM layer from 32 to 1024, doubling in increments. Results, detailed in Table III, indicated a decrease in MAE with an increasing number of neurons, suggesting enhanced predictive capability. However, the reduction in MAE beyond a certain threshold was marginal, accompanied by heightened computational complexity. Consequently, a balance between computational efficiency and predictive accuracy was sought, with 256 neurons deemed optimal. At this configuration, the MAE measured 0.0017, demonstrating excellent performance, even after normalizing all variables within the range of 0 to 1.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_{pred,i} - y_{MARS,i}\right| \qquad \text{Eq. (1)}$$

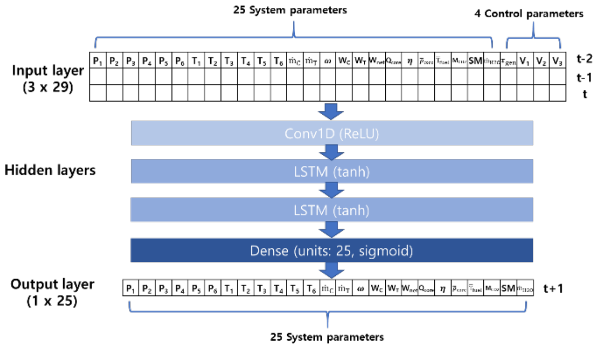

Fig. 10. Structure of the surrogate model

Table III. Test results with different layer sizes

Number of neurons	MAE
32	0.0030
64	0.0019
128	0.0018
256	0.0017
512	0.0016
1024	0.0015

3. Summary and Further Works

In this study, a preliminary investigation was conducted into the development of a time-series surrogate model for the load-following operation scenarios of the sCO_2 cooled KAIST-MMR nuclear power system. The objective was to create an environment suitable for RL-based optimal control. A modified version of the MARS code was utilized as the system analysis tool, and datasets were generated by varying the PI gains of control valves across scenarios with diverse ramp rates of power output fluctuations. Total of 6,393 simulation data points were employed, amounting to 3,842,193 data points. Employing a CNN-LSTM architecture, a time-series prediction model was constructed, and sensitivity analysis on the number of neurons was performed.

This study represents an initial exploration into assessing the performance of predictive models constructed using load-following operation data for the KAIST-MMR. Further research is warranted to refine the approach and address remaining challenges. To achieve this, the authors plan to expand and refine computational scenarios, incorporating a wider range of scenarios to enhance the robustness of the surrogate model. Additionally, efforts will be made to conduct hyperparameter tuning to optimize model performance. These steps aim to create a surrogate model that can more accurately simulate the behavior of the actual system, thereby improving its usefulness for RL-based optimal control strategies.

The developed time-series surrogate model is intended to serve as an environment for RL-based optimal control. Future research will focus on integrating this model into RL frameworks and refining control strategies to enhance the performance and adaptability of the KAIST-MMR nuclear power system in load-following scenarios.

ACKNOWLEDGEMENT

This research was supported by the Challengeable Future Defense Technology Research and Development Program through the Agency For Defense Development (ADD) funded by the Defense Acquisition Program Administration (DAPA) in 2024 (No.912767601)

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