Comparison of Supercritical CO_2 Power System Surrogate Model to test data from KAIST ABC Test Loop

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1. Introduction

A supercritical carbon dioxide (sCO_2) power cycle is a closed Brayton cycle that utilizes sCO_2 as working fluid. In sCO_2 cycles, compression of the CO_2 occurs near the critical point, minimizing both compression work and compressor size. As a result, sCO_2 cycles can achieve high efficiency with small footprint. This makes an sCO_2 power cycle a good candidate for the power conversion system of a small modular reactor (SMR).

For SMR cases, unlike conventional large-scale power systems, where power production is maintained constant, these applications are subject to changes in the load required by the user [1]. Therefore, for sCO_2 systems to become practical in more applications, it must be able to actively respond to changes in load demand. This means that research is needed on the proper control strategy to ensure that the sCO_2 cycle produces the desired output as most efficiently as possible.

Numerous studies have been conducted on control strategies for off-design operation of sCO_2 cycles [2]. However, these control studies are mostly code-based and limited to table-based or PID-based controllers, which are classical control methods. Therefore, it is necessary to design a load-following controller that reflects the nonlinear nature of the supercritical CO_2 cycle and the multi-input-multi-output system model. Currently, controllers based on reinforcement learning are gaining attention for systems that require complex control and are subject to nonlinearities, such as multi-joint robots and unmanned vehicles [3]. Therefore, the application of reinforcement learning-based controllers to the control of off-design operation of sCO_2 cycles is expected to provide efficient and robust control.

For the design of learning-based controllers, it is necessary to simulate fast behaviors that reflect reality. Simulations based on existing thermo-hydraulic analysis codes reflect real-world physical phenomena well, but they can become too slow due to the continuous calculation of fluid equations.

In this paper, a surrogate model is proposed to solve this problem. The method is to train the data obtained through the existing thermo-hydraulic analysis code with a surrogate, and then uses the surrogate as a learning environment to create a reinforcement learning-based controller. Through the surrogate, the simulation can be accelerated during the controller training process. To give validity to this approach through surrogate, it is necessary to validate the surrogate first. In this paper, a surrogate model was built using data generated from MARS-KS, a thermo-fluid analysis code, and the surrogate was validated using the Autonomous Brayton Cycle (ABC) test loop, an integrated test facility for sCO_2 cycle at KAIST.

2. Methods and Results

This section describes the design and experimental validations of a surrogate model.

2.1 ABC Test Loop

The ABC Test Loop is a simple recuperated Brayton sCO_2 cycle test facility. This research facility has been constructed to perform integrated testing of a simple recuperated sCO_2 power cycle. It consists of the active magnetic bearing supported turbo-alternator compressor (AMB-TAC), a printed circuit heat exchanger (PCHE) recuperator, an electric cartridge heater, and a PCHE and shell-and-tube precooler. The front view of the ABC test loop is shown in Figure 1.

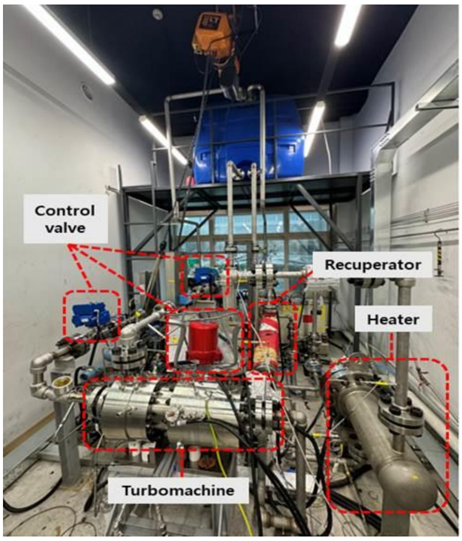

Fig. 1. Front view of the ABC test loop

Data acquisition for the ABC test loop is performed using LabVIEW. The input and output signals of the ABC test loop are recorded with the time resolution of 0.1 seconds. External programming languages and libraries are integrated into the system so that physical properties and control logic can be calculated in real time. The ABC Test Loop is equipped with motor driven valves for control experiments and turbine experiments.

Currently, there is one valve at the front and back of the compressor, a valve to bypass the turbine, a venting valve, and a valve connected to the inventory tank. All these valves are electric, which was chosen to reduce vibration from hydraulic or pneumatic valves and to simplify the experimental rig without subsystems.

2.2 MARS-KS Model

The MARS-KS code is a nuclear thermo-hydro safety analysis code. As the MARS-KS code was originally designed for water system analysis, the KAIST research team modified the MARS code as the following to better predict the behavior of the system with sCO_2 conditions: (1) implementing accurate physical properties of CO_2 using NIST's REFPROP database, (2) adding PCHE heat transfer correlations to the thermal structure, and (3) predicting the off-design performance of the turbine and compressor based on the turbomachinery map [4]. This modified MARS-KS code has been validated and verified with experimental data.

The entire system of the ABC test loop was modeled using MARS-KS. To evaluate the MARS-KS modeling, comparisons between the experiments and the MARS-KS code were performed for two scenarios: one that varies the torque of the AMB-TAC, and one that adjusts the turbine bypass valve. To test the control elements, the turbomachinery speed of the ABC Test Loop was fixed at 18,000 rpm, and the system was allowed to reach steady-state with the compressor inlet temperature controlled at 35°C. After steady state was achieved, the system's response to torque input control and turbine bypass control was tested [5].

Figures 2 and 3 compare the results predicted by MARS-KS with the experimental results of the ABC Test Loop. In Figure 2, the input torque of the AMB-TAC is varied, and in Figure 3, the opening rate of the turbine bypass valve is varied. Both cases show that the ABC Test Loop modeled by MARS-KS and the ABC Test Loop of the actual experiment have comparable results, which means that the MARS-KS model simulates the real sCO_2 system reasonably well.

2.3 Surrogate Model

To predict the system dynamics, a time-series surrogate model was developed based on the simulation results of the ABC Test Loop implemented in MARS-KS. The surrogate model was developed based on various scenarios of changing the inverter torque. Each scenario was simulated for 600 seconds, and a total of 10,890 different scenarios were generated to produce a dataset.

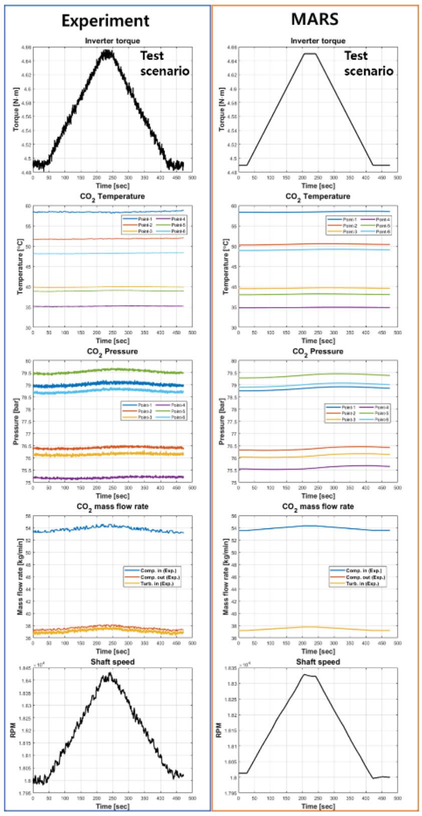

Fig. 2. Comparison between experiment and MARS-KS at torque input control [5]

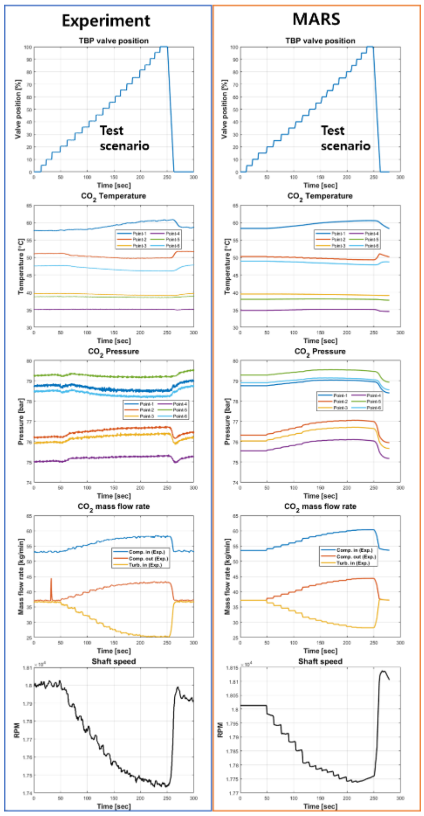

Fig. 3. Comparison between experiment and MARS-KS at turbine bypass control [5]

The surrogate model was developed using the rolling window forecast method to ensure the accuracy of time-series prediction. The window size was set to 3, and the time interval was set to 5 seconds. The supervised learning model for training the surrogate model is Long Short-Term Memory (LSTM), which is known to be good at predicting time-series data. In addition, an attention layer was added to improve the performance of the LSTM model. Figure 4 shows the structure of the surrogate model of the ABC Test Loop.

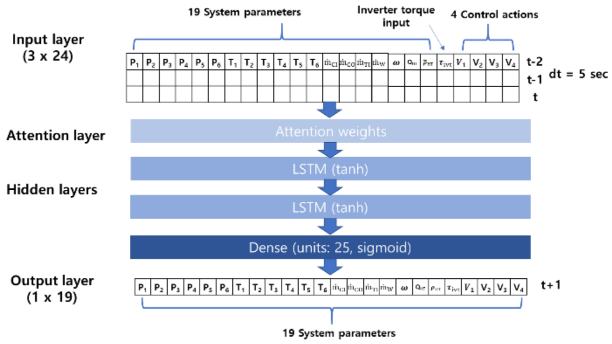

Fig. 4. Structure of the surrogate model for ABC Test Loop [5]

2.4 Comparison with Experimental Data

The surrogate model developed with the MARS-KS code was validated by comparing it with actual experimental data. The comparison between the surrogate model and ABC Test Loop was performed using two experimental results, AMB-TAC torque change and turbine bypass valve opening change, which were used to compare the dynamics between MARS-KS code and ABC Test Loop. For the comparison, the experimental data was sampled at 5-second intervals. The experimental data was used as the value of the input layer, and the value of the output layer was obtained with the surrogate. The values of the output layer are the system parameters one time step after the final time of the given input, i.e. 5 seconds later. The output values were predicted using only the input values and the surrogate, and no additional information such as property tables or system dynamics was provided.

Figure 5 and Figure 6 compare the results predicted by surrogate and the experimental results of the ABC Test Loop. The solid line shows the experimental results, and the dashed line shows the results predicted by surrogate. Figures 5 and 6 correspond to Figure 2 and Figure 3, respectively. In Figure 5, the input torque of the AMB-TAC is varied, and in Figure 6, the opening speed of the turbine bypass valve is varied. In both cases, the dynamics of the ABC Test Loop predicted by time-series surrogate model is similar to that of the ABC Test Loop in the actual experiment. For both the inverter torque variation and the turbine bypass valve opening variation, the error between the surrogate predictions and the experimental results for temperature, pressure, and shaft speed were within 2%. However, the error for flow rate was large with errors of up to 25% for the inverter torque variation and up to 6% for the turbine bypass valve opening variation. Due to the system characteristics of the ABC loop, the flow is proportional to the shaft speed because the flow is only caused by the action of the AMB-TAC. Therefore, the fact that the shape of the flow is the same as the shape of the shaft speed in the experimental results means that the flow measured in the experiment is consistent. Therefore, it is not that the surrogate fails to predict the flow because the flow is measured incorrectly due to the experimental design process or the accuracy issue of the flow measurement sensor. In other words, it is necessary to improve the performance of the surrogate to increase the accuracy of the flow prediction. This can be done by adjusting hyperparameters such as the number of layers or by increasing the training time.

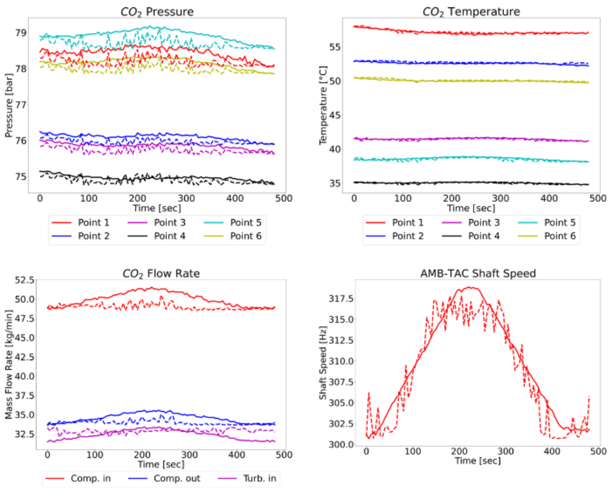

Fig. 5. Comparison between experiment and surrogate at torque input control

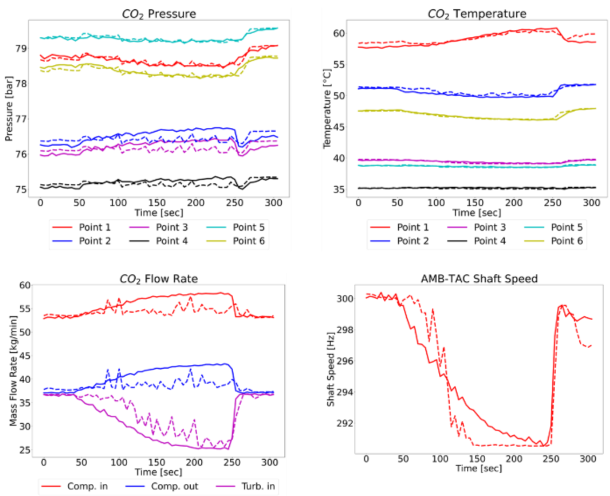

Fig. 6. Comparison between surrogate and MARS-KS at turbine bypass control

Compared to the experimental data, the surrogate model predicted the temperature and pressure of the system with an error of 2%. In other words, the surrogate model performed well in predicting the thermodynamic state of the system. On average, the time taken to predict the outcome of the next time step using surrogate was 0.7 milliseconds. This is significantly faster than the computational speed of MARS-KS. This means that the surrogate model can be used to quickly and accurately predict what state the real system will be in after 5 seconds. A limitation is that the system's flow prediction error was significant. However, the trend was similar, so there is room for improvement.

3. Conclusions

Learning-based control is expected to help with autonomous operation of various nuclear systems, not just supercritical CO_2 cycles. To create a reinforcement learning-based controller, it is important to build an environment in which the controller can learn. The current thermal fluid simulation environment, MARS-KS, is limited in terms of speed. Therefore, a surrogate model was developed to accelerate the learning of the controller.

To analyze the performance of this surrogate model, the ABC test loop, an sCO_2 cycle experiment facility, was used to compare experimental results and surrogate predictions. The comparison showed that the surrogate model reasonably predicts the thermodynamic properties of the system within a short computational time. Therefore, using surrogates is a suitable methodology for designing a reinforcement learning-based controller. Furthermore, utilizing a surrogate model will help to predict what will happen to the system in advance, reducing the likelihood of accidents or making it work more efficiently.

ACKNOWLEDGEMENT

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