# Comparative Evaluation on PI controller Optimization using SPACE and MARS-KS for i-SMR design

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## 1. Introduction

To ensure stable operation of the innovative small modular reactor (i-SMR) during performance-related design basis events (PRDBE), such as a ramp change or a step change of turbine load, an optimization of the control system is required.

A machine-learning-based PI controller optimization framework is proposed and currently under development, in which a large number of transient simulations, generated using the maximin Latin hypercube sampling (LHS) method, are employed to train surrogate models for efficient PI gain tuning.

Owing to its computational efficiency, MARS-KS is adopted as the primary computational model in this optimization approach, whereas SPACE code, which is being used in the performance analysis of the i-SMR, is computationally disadvantageous for exhaustive simulations due to its 9-equation formulation [1].

In this study, the feasibility of applying MARS-KS code, which adopts 6-equation formulation [2], as a faster alternative code for producing large training datasets for the proposed PI controller optimization framework is evaluated by comparative analyses between SPACE and MARS-KS.

The objective of this study is to compare the control system performance predicted by SPACE and MARS-KS under the identical combination of PI gains and to assess whether the PI gains optimized using MARS-KS are directly applicable to SPACE without any significant degradation in the control performance.

## 2. Methodology

### *2.1. Assumptions*

As a reference transient, a 100-20-100% turbine load ramp change with a rate of 5%/min was selected. It is assumed that pressurizer pressure and water level are controlled at fixed setpoints by a heater and charging/letdown flow rate. In addition, the main steam pressure is assumed to be controlled at a fixed setpoint by main feedwater flow rate.

The reactor regulation system, which controls the temperature of the coolant according to a predefined temperature program by the control rods, is not assumed in this study and the load-following is achieved solely by the moderator temperature feedback.

### *2.2. Sampling of PI gains*

To produce the training data set for the machine-learning-based PI controller optimization framework, 10,000 combinations of PI gains ( $K_P, K_I$ ) for a pressurizer heater demand, charging/letdown demand, and main feedwater demand were generated by using a maximin LHS method and control performances of all 10,000 combinations were evaluated using MARS-KS code.

From these cases, 124 cases were randomly selected for comparative analyses to statistically assess the code-to-code consistency within the sampled gain space. The number of sample cases was determined by Wilks' formula to find the 95/95 upper and lower bounds of the relative difference in between two computational models [3].

### *2.3. Metric of the Control Performance*

Two types of performance metrics are considered: the integral of squared error (ISE) of the controlled variables and the integral of squared control action (ISU). ISE is evaluated separately for each control objective (pressurizer pressure/level and main steam pressure), while ISU is evaluated separately for each control action (pressurizer heater power, charging/letdown flow rates, and feedwater flow rate).

$$\mathrm{ISE}_{obj} = \int_0^T e_{obj}(t)^2 dt \qquad (1)$$

$$e_{obj}(t) = \frac{x_{obj}(t) - x_{setpoint}}{d\left(x_{obj}(t)\right)} \qquad (2)$$

$$\mathrm{d}\left(x_{obj}(t)\right) = \begin{cases} x_{setpoint} - x_{min}, & x_{obj}(t) < x_{setpoint} \\ x_{max} - x_{setpoint}, & x_{obj}(t) \geq x_{setpoint} \end{cases} \qquad (3)$$

$$\mathrm{ISU}_c = \int_0^T \left(\frac{u_c(t)}{u_{c,max}}\right)^2 dt \qquad (4)$$

The overall performance of the control system during the transient is quantified by a quadratic cost function

($J_{LQR}$), which is defined as the sum of all ISE and ISU terms over the time period of the transient.

$$J_{LQR} = \sum_{obj} \mathrm{ISE}_{obj} + \sum_{c} \mathrm{ISU}_c \quad (5)$$

The relative difference in $J_{LQR}$ is used as the metric to quantify the code-to-code discrepancy for a given combination of PI gain values and is calculated as the percentage difference of the SPACE results with respect to the MARS-KS results.

$$\text{relative difference} = \frac{J_{LQR,SPACE} - J_{LQR,MARS}}{J_{LQR,MARS}} \quad (6)$$

*2.4. Comparative Analyses*

The 95/95 upper and lower bounds of the relative difference in $J_{LQR}$ are determined based on the third highest and the third lowest values from the 124 samples respectively. Additionally, the statistical characteristics of the relative difference among the sampled cases are evaluated to assess the applicability of the PI gains optimized using MARS-KS to SPACE.

Furthermore, SPACE analysis is performed for the optimized combination of PI gains identified through MARS-KS analyses on 10,000 combinations which are sampled by maximin LHS method. The thermal-hydraulic behaviors and the control performance are compared with those of the MARS-KS results to confirm that they are directly applicable to SPACE without any significant degradation in the control performance.

### 3. Results and Discussion

The statistical characteristics of the relative differences are summarized in Table 1. The 95/95 upper and lower bounds of the relative difference of control performance, determined from the 124 sampled cases, are 831% and -83%, respectively. A significantly large upper bound originates from a few cases with a combination of PI gains which leads to unstable or oscillatory behaviors of the controlled variables. These cases with inadequate PI gains, however, are deemed practically irrelevant regarding the purpose of PI gain optimization.

When the upper and lower 10% of the cases are excluded, the mean relative difference is significantly reduced (from 133% to -28%). According to the results, SPACE predicts slightly better control performance (lower $J_{LQR}$) for the identical PI gain combinations. This tendency is presumed to arise from unintended minor differences in MARS-KS modeling, which causes relatively larger pressure oscillations.

Subsequently, SPACE analysis on the reference transient is performed with the optimum PI gain combination determined by MARS-KS. The control performance predicted by the two codes is reasonably similar, with a relative difference of 18.3% and the thermal-hydraulic behaviors are comparable as shown in Figures 1-4.

Table I: Statistical Characteristics of the Relative Difference of the Control Performance

| | All samples (n = 124) | Upper/lower 10% excluded (n = 100) |
|---|---|---|
| Mean | 133% | -28% |
| Median | -29% | -29% |
| 25th percentile | -73% | -70% |
| 75th percentile | 4% | -2% |
| 3rd highest | 831% | Not applicable |
| 3rd lowest | -83% | Not applicable |

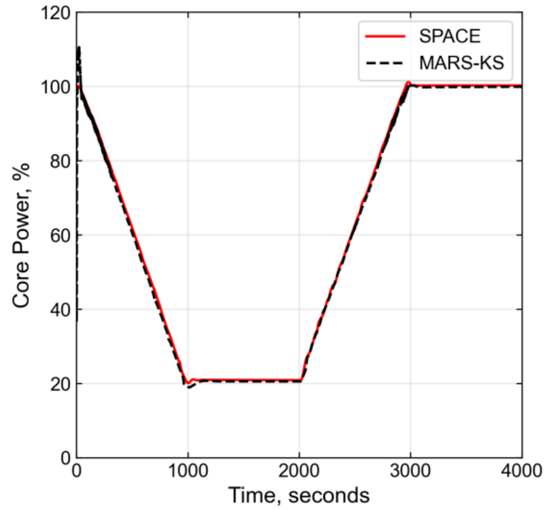


Fig. 1. Core Power (MARS-Optimized Case)

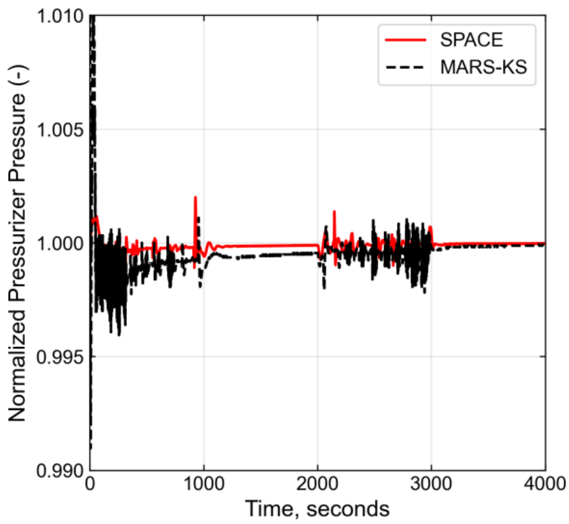


Fig. 2. Pressurizer Pressure (MARS-Optimized Case)

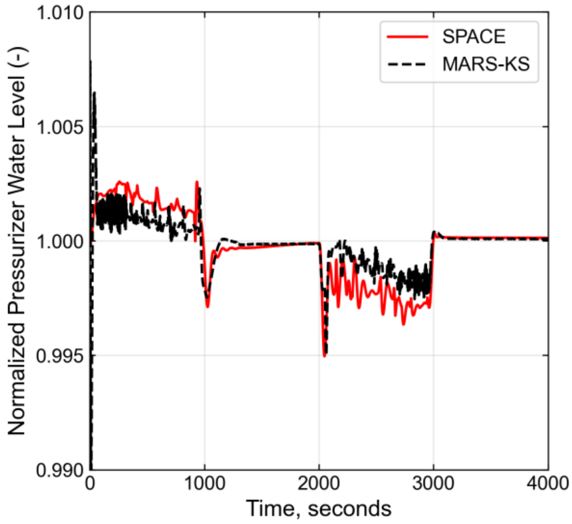


Fig. 3. Pressurizer Water Level (MARS-Optimized Case)

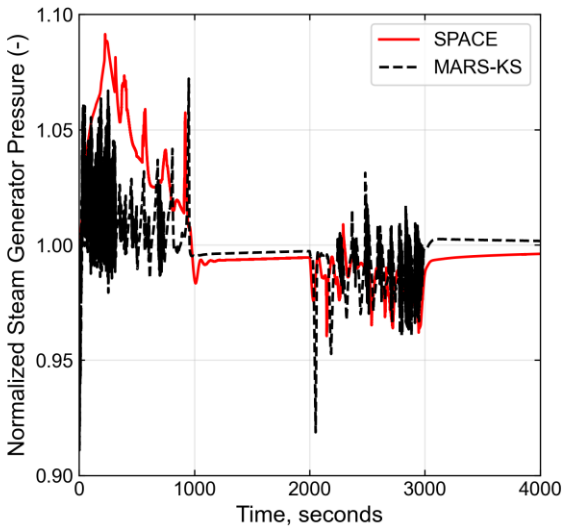


Fig. 4. Steam Generator Pressure (MARS-Optimized Case)

## 4. Conclusions and Future Works

In this study, the applicability of MARS-KS as an alternative computational model for the optimization of the i-SMR control system is evaluated by comparative analyses between SPACE and MARS-KS.

Although the 95/95 upper bound of the relative differences appears relatively large due to unstable or oscillatory behaviors in a few cases, these regions of improper PI gains are not practically relevant for PI controller optimization. With upper and lower 10% excluded, the control performance predicted by SPACE and MARS-KS is shown to be reasonably consistent.

Furthermore, the combination of PI gains, optimized using MARS-KS based on 10,000 samples by maximin LHS, is shown to produce comparable thermal-hydraulic behaviors when it is directly applied to SPACE, with a relative difference in control performance less than 20%.

These results demonstrate that the predictions on the control performance for combinations of PI gains at or near the optimal point are consistent between two codes. Thus, MARS-KS can serve as an efficient alternative for producing large training datasets for a machine-learning-based PI controller optimization framework in i-SMR, significantly reducing computational cost while maintaining accuracy. The computational time using MARS-KS was observed to be approximately 80% lower than that of SPACE in the present study; however, the exact reduction may vary depending on the computational environment and implementation conditions.

Future work will focus on reducing the modeling discrepancies between the two codes and further extending the analyses to other PRDBEs.

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## REFERENCES

[1] S.J. Ha, C.E. Park, K.D. Kim, and C.H. Ban, Development of the SPACE code for nuclear power plants, Nuclear Engineering and Technology, Vol.43, p.45-62, 2011.

[2] J.J. Jeong, K.S. Ha, B.D. Chung, and W.J. Lee, Development of a multi-dimensional thermal-hydraulic system code, MARS 1.3.1, Annals of Nuclear Energy 26 (1999), 1611-1642.

[3] N.W. Porter, Wilks' formula applied to computational tools: A practical discussion and verification, Annals of Nuclear Energy 133 (2019), 129-137.