

Performance Optimization Method of Steam Generator Liquid Level Control Based on Hybrid Iterative Model Reconstruction [†]

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Abstract: The steam generator is an important price of energy exchange equipment for nuclear power plants, and the level control of steam generator plays a key role in the stable operation of the plants. To improve the level control performance of the steam generator, it is necessary to adjust the parameters of the level control system during the commissioning process of nuclear power plants. However, the parameter tuning process heavily dependent on engineers' experience, requires a large amount of operational history data, and is difficult to ensure optimal performance. To address these issues, this paper proposes a hybrid iterative model reconstruction-based steam generator level control performance optimization method, based on the idea of data-driven optimization. The method proposes a fusion idea and implementation mechanism in which process data and hybrid model are jointly driven under the data-driven framework to maximize the advantages of different modeling mechanisms to achieve the performance optimization of steam generator level control system. The method first constructs the initial data set with a small-sample Latin-square experiment design, and then, builds two different fitting models, SVM and Kriging, based on the initial data set respectively, under the hybrid model fusion idea. After that, the particle swarm optimization algorithm is used to calculate the optimal point of the current valid model, and the optimization process is controlled by establishing the iteration termination judgment based on the historical iteration data. Then, the current iteration point is used to dynamically reconstruct the two types of models. Finally, the two types of models are dynamically reconstructed using the current iteration points. The above process is iterated until the optimal iterative process of the system is satisfied. From the experimental results, it can be seen that compared with two types of single-model optimization methods, this method can reduce the iteration final value by 13.57% and 16.27% with a slightly increased number of iterations. These results indicate that this method can significantly improve the efficiency of optimizing the control performance of the steam generator liquid level.

Keywords: performance optimization; steam generator level control; hybrid model; small-sample modeling

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1. Introduction

The steam generator (SG) is one of the crucial prices of equipment in pressurized water reactor nuclear power plants [1,2]. During the operation of the SG, a significant deviation between the actual and set liquid levels may result in equipment failures that can adversely impact production efficiency [3,4]. The SG water level process exhibits highly nonlinear and time-varying characteristics, and traditional fixed-parameter level

control methods lack optimization, adaptivity, self-learning, and other functions. To enhance the water level control performance of the steam generator, it is necessary to adjust the parameters of the level control system during the commissioning and operation processes of the nuclear power plant. The parameter tuning method based on engineer experience has drawbacks such as high cost and low efficiency. The swarm intelligence optimization method without relying on the model achieves the automation and intelligence of parameter optimization, and the optimization cost is high, and the feasibility and practicability for engineering are poor [5–7]. The model-based optimization method contains the advantages of swarm intelligence optimization methods that are not model-based. However, establishing an accurate control system model is difficult, which makes it difficult to ensure the optimality of the tuning parameters. None of the above parameter optimization methods can adequately solve the problem of parameter tuning in steam generator level control systems [8–14]. To address the challenges encountered in the parameter tuning process of the steam generator liquid level control system, it is necessary to find an efficient optimization method for parameter tuning.

Based on the above analysis, to address the problem of model errors in model-based optimization methods, this paper constructs an initial small sample dataset through experimental design, and uses SVM and Kriging models constructed from the small sample dataset as initial models. To overcome the issue of requiring a large number of experiments to ensure model accuracy, this study utilizes optimization iteration process data to guide the optimization process within a data-driven framework [15–18]. By continuously updating the modeling dataset with the process data generated during the iteration process and using the updated dataset to establish a more accurate model in a reconstructed manner.

2. Performance Optimization of the Steam Level Control System

SG level control process is by changing the feed water flow to achieve the current steam generator level height to meet the set requirements [16]. The framework for performance optimization of the steam generator liquid level control system as shown in Figure 1. This optimization framework consists mainly of three parts: the steam generator water level control system, performance evaluation, and optimization algorithm.

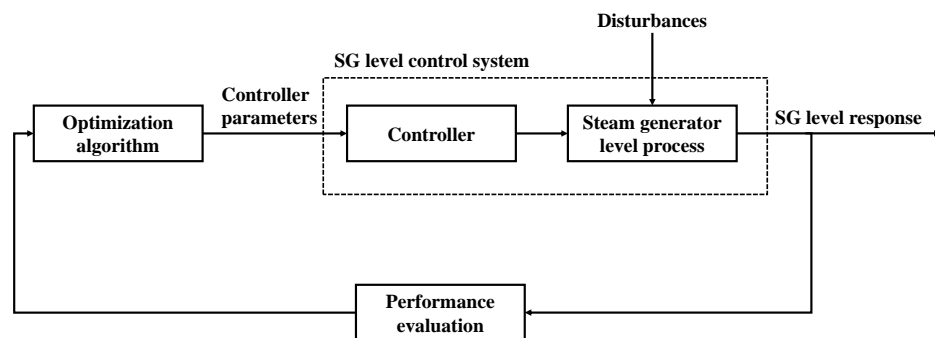


Figure 1. General structure of the steam generator level control system.

In the optimization process of the SG level control system. Firstly, the control parameters are input into the SG level control system and the level response is obtained. Secondly, the corresponding level response of the current control parameters is analyzed for the control performance. The performance index formula is as follows:

$$ITAE(Ig) = Ig \int_0^T t |e(t)| dt, \tag{1}$$

where $e(t)$ represents the deviation between the actual water level and the set water level, t represents time. while T is the evaluation period.

Finally, if the performance index does not meet the evaluation criteria of optimization termination, the control parameters are set by the optimization algorithm to achieve the performance optimization of the SG level control system.

3. Optimization Method Based on Hybrid Iterative Model Reconstruction.

3.1. Hybrid Model Idea

Currently, there are mainly two problems with model optimization methods: (1) High-precision models require a large number of sample datasets to be established. (2) Single models exhibit low fitness during the optimization process.

To address the aforementioned problem, this paper proposes a hybrid modeling method based on the traditional single-model optimization concept. This method is inspired by how individuals perceive the world in real life. In the process of personal understanding of the world, learning to construct a complete world model is mainly relied upon. However, relying solely on the information in one book to establish a personal worldview can often lead to bias (traditional single-model optimization idea). Therefore, when the information in one book does not meet the needs of personal worldview building, individuals should read books of other types and use the information in different books to establish a more accurate worldview (hybrid-model optimization idea).

This paper proposes a data-driven hybrid iterative model reconstruction and optimization method based on the combination of data-driven and hybrid model ideas. The method is applied to the optimization of the liquid level control performance of a nuclear power plant steam generator, as shown in Figure 2.

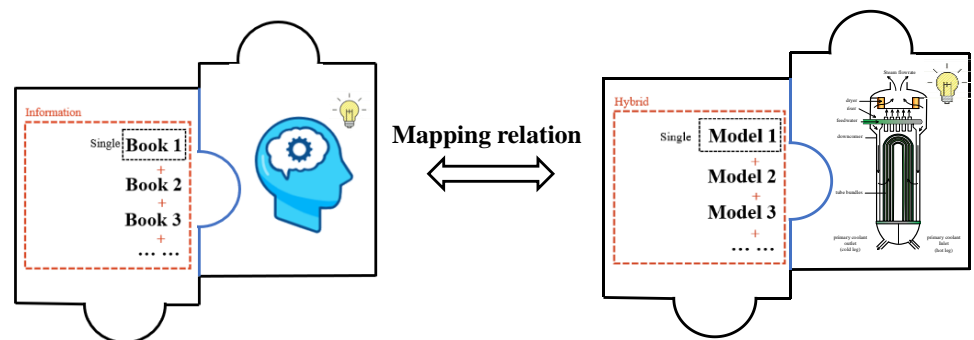


Figure 2. The mapping relationship between hybrid model idea and SG performance optimization.

3.2. Hybrid Iterative Model Reconstruction Optimization Framework

Based on the characteristics of the optimization problem in Equation (1), this paper combines the data-driven optimization idea with the model optimization idea and designs a hybrid iterative model reconstruction optimization framework as shown in Figure 3.

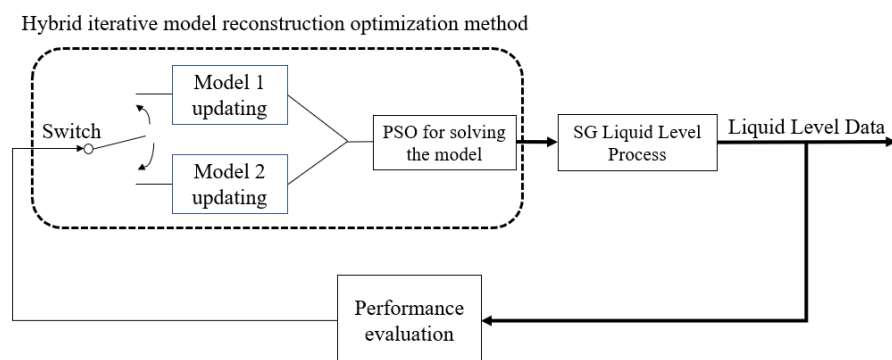


Figure 3. The framework of hybrid iterative model reconstruction optimization.

This framework combines data-driven ideas, utilizes system operation process data, and introduces running data into the model reconstruction process to achieve high-precision model establishment through a small number of samples. Meanwhile, the framework also combines the hybrid model idea to utilize different model building methods and adopts an accuracy-first strategy to select the most effective model in the current batch, thus maximizing the utilization of different models' fitness in the optimization process.

3.3. The Process of Hybrid Iterative Model Reconstruction Optimization

The specific process of the hybrid iterative model reconstruction and optimization is shown in Figure 4, and the specific steps are as follows:

1. Numerical initialization; Determine the parameters to be optimized in the control system and their corresponding feasible domains, and set the termination criterion for the iteration.
2. Generate initial model samples; To ensure the randomness of the initial sample within the value range, this paper uses Latin hypercube sampling for initial sample extraction. This method divides the value range of each dimension into several equal parts and randomly selects one point from each part to ensure an even distribution of values in each dimension.
3. Hybrid model construction; SVM and Kriging models are constructed separately based on the modeling data samples.
4. Model selection; Calculate the accuracy of the two types of models, and select the high-precision model as the effective model for the current iteration batch through the model selection mechanism.

The formula for calculating the model's accuracy is shown in Equation 2:

$$n = \left(1 - \frac{|x - \mu|}{\mu}\right) \times 100\% , \quad (2)$$

In the Equation, n represents the model accuracy, x represents the model predicted value, and μ represents the response actual output value.

The model selection mechanism is as follows: if the accuracy of model 1 is higher at the current iteration point, then model 1 will be used in the next iteration; if the accuracy of model 2 is higher at the current iteration point, then model 2 will be used in the next iteration, as shown in Equation (3).

$$m = \begin{cases} m_1 & p_1(k) \geq p_2(k) \\ m_2 & p_2(k) > p_1(k) \end{cases} ' \quad (3)$$

In the Equation (3), m represents the model used in the $k + 1$ iteration, m_1 represents model 1, m_2 represents model 2, $p_1(k)$ represents the model accuracy of model 1 in the k th iteration, and $p_2(k)$ represents the model accuracy of model 2 in the k th iteration.

5. Calculating the optimal point of the model using PSO; The particle swarm optimization algorithm is used to calculate the optimal point of the effective model in the current iteration batch [19].
6. The liquid level response process; The SG liquid level control system experiment is performed with the optimal point of the effective model in the current iteration batch, and the performance of the control system is analyzed. The performance evaluation index of the control system is shown in Equation (1).
7. Termination criteria for iteration; Check whether the performance indicator meets the pre-set optimization termination criteria [16]. If it meets, stop the current optimization process and iteration, output the current parameter values and performance;

if not, update the modeling data set using the experimental data of the SG liquid level control system and return to step 3 to continue a new round of iterative optimization.

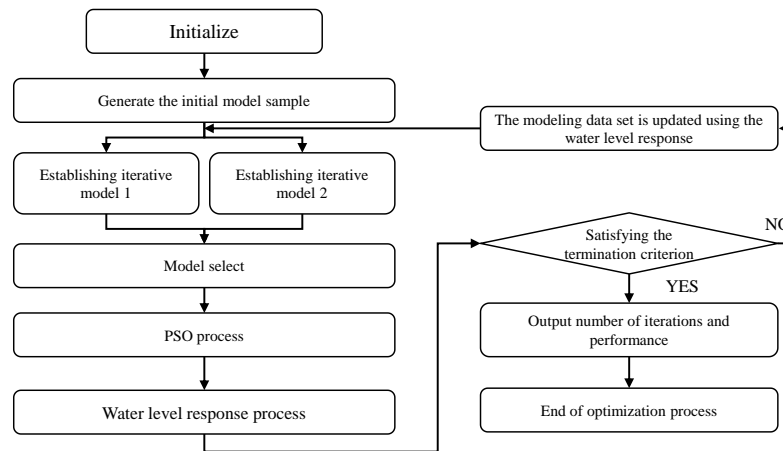


Figure 4. Hybrid iterative model reconstruction implementation mechanism.

4. Results and Discussions

4.1. Simulation Experiment Settings

For ease of comparison, all experiments will adopt the same iteration termination control strategy and the same initial point within the feasible domain of SG controller parameters.

4.2. Research on Small-Sample Fitting Models

To implement the optimization framework described above, the selection of model 1 and model 2 in Figure 3 is performed first. In this study, based on the reliability research of small sample modeling. In this paper, Kriging model and SVM model are used as model 1 and model 2 respectively in the optimization framework [19].

4.3. Effectiveness Test

To compare the two single-model optimization methods of the Kriging model and SVM model with the optimization method based on the Kriging model and SVM model’s hybrid iterative model reconstruction, as shown in Figure 5a. Observe the model accuracy data of the iterative model method, as shown in Figure 5b.

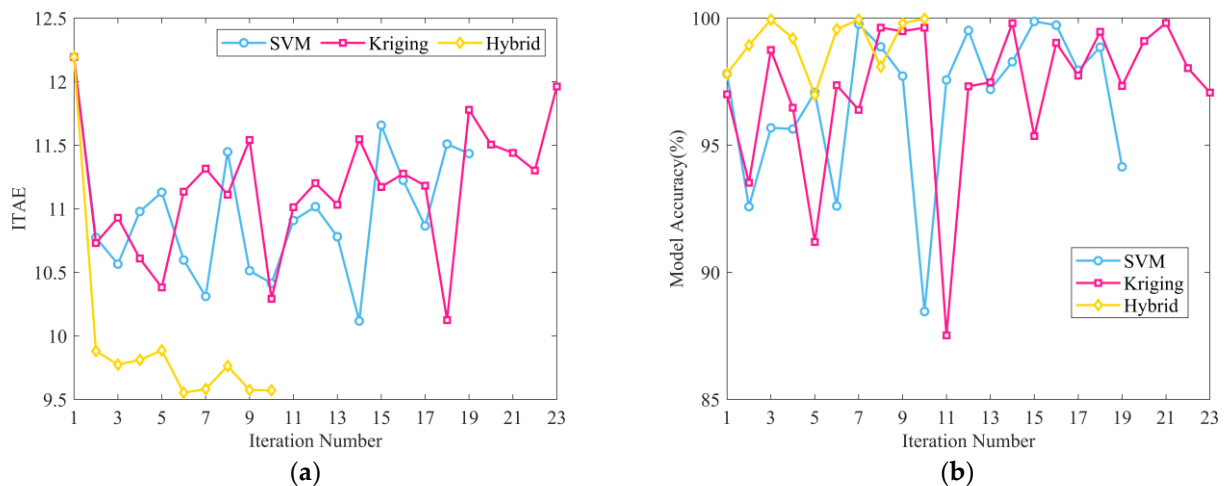


Figure 5. (a) Performance optimization curve; (b) Model accuracy curve.

From Figure 5, it can be seen that the two single-model optimization methods of Kriging and SVM require 10 and 23 iterations, respectively, while the hybrid iterative model reconstruction optimization method based on Kriging and SVM only requires 10 iterations, which can quickly approach the optimal solution. In addition, as the number of iterations increases, the model accuracy in the hybrid iterative model reconstruction method remains above 95%, while the model accuracy in the two single-model optimization methods varies greatly. This indicates that the hybrid iterative model reconstruction method has high optimization efficiency.

4.4. Efficiency Test

Through the above experiments, it has been demonstrated that the hybrid iterative model reconstruction optimization method is effective for performance optimization of the SG level system. However, in order to reduce the impact of algorithmic randomness on optimization results, 25 batches of experiments were conducted for the three optimization methods, and the number of iterations and the optimal value of iterations are shown in Figure 6.

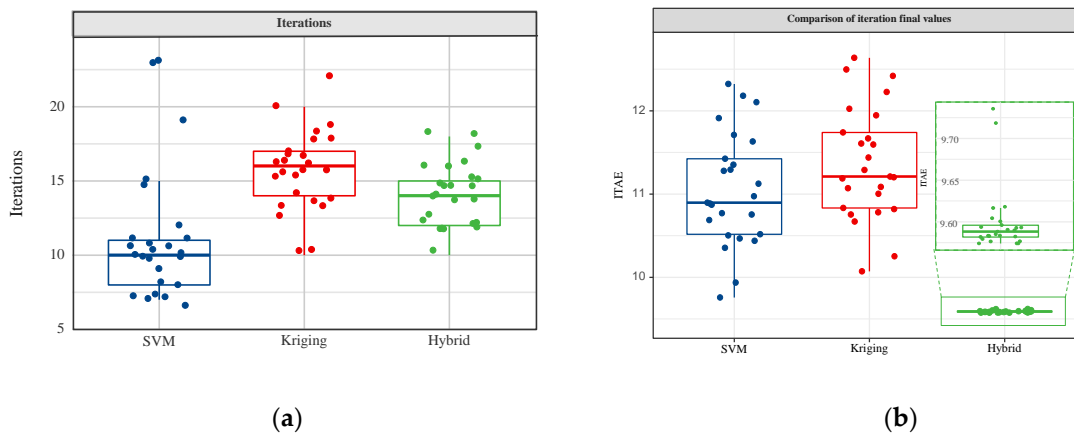


Figure 6. (a) Iterations count statistics; (b) Optimization results count statistics.

In the efficiency test, the average number of iterations for the hybrid iterative model optimization method was 13.86, which increased by 26.7% compared to the optimization methods of SVM and Kriging, and decreased by 17.75%, respectively. The average final iteration value for this method was 9.63, which decreased by 13.57% and 16.27%, respectively, compared to the other two methods.

Although the hybrid iterative model reconstruction optimization method based on the Kriging model and SVM model performs better in terms of optimization results, the optimization efficiency obtained through it has not improved. The performance of the hybrid iterative model reconstruction optimization method in terms of optimization efficiency is slightly worse than that of the single-model optimization method based on the SVM model. However, this difference is very small, so we can still conclude that the hybrid iterative model reconstruction optimization method based on the Kriging model and SVM model sacrifices a little optimization efficiency in exchange for the improvement of performance indicators. Therefore, the hybrid iterative model reconstruction optimization method based on the Kriging model and SVM model is still an effective method.

5. Results and Discussions

In this study, a hybrid iterative model reconstruction optimization method was proposed and applied to the performance optimization of the SG level control system in a steam generator. By introducing the fusion idea and implementation mechanism of process data and hybrid models driven together under the data-driven framework, the hybrid

iterative model reconstruction optimization method can achieve the performance optimization of the control system. This method not only maximizes the advantages of different modeling mechanisms but also fully utilizes historical information generated during the optimization process to participate in the optimization process. Simulation experiments have shown that this method, compared with the single-model optimization method, has increased the iteration number by 26.7% and reduced it by 17.75%, respectively, and reduced the final iteration value by 13.57% and 16.27%, respectively.

Therefore, it can be concluded that the hybrid iterative model reconstruction optimization method is an efficient method for performance optimization of the SG level control system. This method can be applied to other similar controller parameter optimization problems in various nuclear power plant process control systems.

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Abbreviations

SG	Steam Generator
SVM	Support Vector Machine
BP	Back Propagation
PID	Proportional-Integral-Derivative
ITAE	Time multiplied by Absolute Error

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