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A Multi-Source Hybrid Data-Driven Optimization Method for Steam Generator Level Control Based on Model Accuracy Gradient Estimation

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Abstract: Steam generator (SG) is the key equipment in the energy transfer process of nuclear power plant, and its level control is particularly important for the safe and stable operation of nuclear power plant. Adjusting control parameters is subject to various factors such as engineer experience and time costs, making it difficult for control systems to achieve optimal control performance. This paper proposes a multi-source hybrid data-driven optimization method based on model accuracy gradient estimation (MHDO-MAGE) according to the data-driven idea and stochastic approximation algorithm. The gradient estimation method is determined by evaluating the accuracy of the model and selecting either the model gradient estimation or online gradient estimation. This method combines model-driven and data-driven optimization methods during the iterative optimization process. The simulation results show that this method has better optimization performance than the traditional Simultaneous Perturbation Stochastic Approximation (SPSA), and can significantly improve the efficiency of steam generator level control performance optimization.

Keywords: Nuclear power plant; Steam generator; Multi-source hybrid data-driven; SPSA

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1. Introduction

The steam generator (SG) is a critical equipment in nuclear power plants and directly relates to the safe and stable operation of the plant [1]. Therefore, controlling the level change of the SG within a predetermined range is of great significance for the stable operation of nuclear power plants. The SG level control system of nuclear power plants generally adopts a fixed parameter Proportion Integration Differentiation (PID) controller [2]. Currently, the most commonly used method for PID parameter tuning is still the traditional method [3]. However, these methods are limited by issues such as reliance on experience, time-consuming tuning optimization processes, and inability to achieve optimal control processes. Moreover, the parameter tuning process increases the number of iterations and actual optimization cost.

This article proposes a performance optimization method for the SG level control system in nuclear power plants, called the Multi-Source Hybrid Data-Driven Optimization Method based on Model Accuracy Gradient Estimation (MHDO-MAGE). Taking into account the actual optimization cost and the accuracy of prior models, the method sets a model accuracy threshold. When the model accuracy during the running process exceeds the threshold, model gradient estimation is used. Otherwise, online experiments will be conducted for gradient estimation. The ultimate goal of optimization is to reduce the number of iterations and lower the optimization cost.

2. SGLCS performance optimization

The overall structural framework for SG level control system (SGLCS) performance optimization is shown in Figure 1, consisting of three components: SGLCS, operational performance evaluation, and the optimization algorithm.

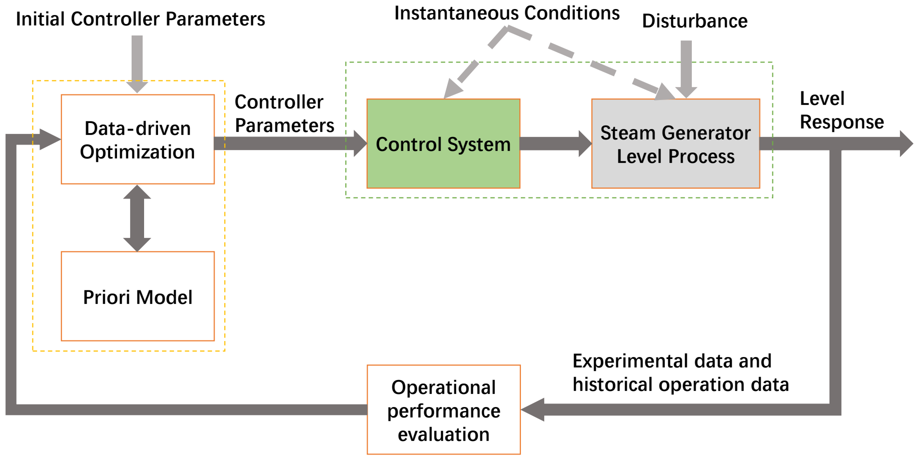

Figure 1. The framework of the multi-source hybrid data-driven SG level control system performance optimization method based on model accuracy gradient estimation

2.1. SG Level Control System

Single pulse control systems are not suitable for pressurized water reactor steam generators with high power and "false level". Double pulse systems use steam flow signal feedforward compensation to solve the problem of "false level," but disturbance generated by given water flow requires level error signal to be adjusted through PID controller, resulting in lag. Therefore, a common SGLCS uses a three-pulse series PID control system to further compensate for the lag caused by feedwater flow disturbance and achieve balance between feedwater flow and steam flow [4]. This article adopts the SG liquid level model based on E. Irving [5]. The framework of SGLCS is shown in Figure 2.

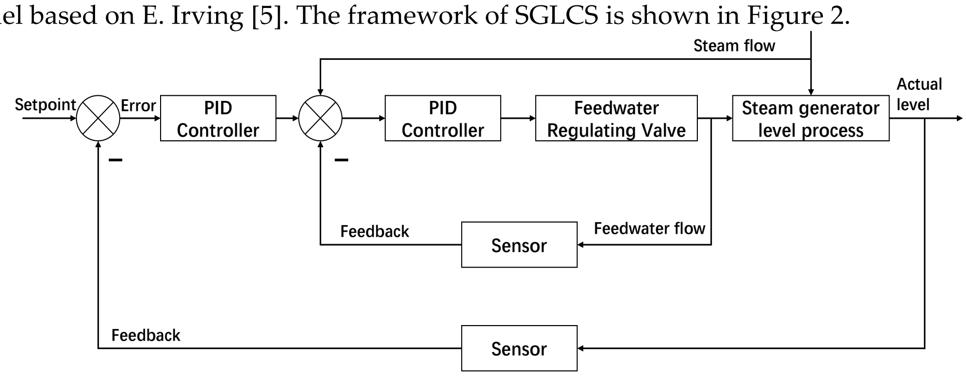

Figure 2. The structural diagram of the three-pulse series PID control system.

2.2. Operational performance evaluation

The operational performance evaluation system obtains and stores data from the level response process, and the calculated values of performance evaluation metrics can be used to assess the control performance induced by current control parameters. In this paper, the control system performance evaluation metric adopts the integral of time multiplied by the Integrated Time and Absolute Error (ITAE), which evaluates the characteristics of the step response transient curve [6], as shown in the following formula:

$$ITAE = \int_0^{T_s} t\left|e(t)\right| dt \quad (1)$$

Where e(t) is the deviation between expected output and actual output, and *Ts* is the simulation time.

2.3. Optimization Method

Once the structure of the steam generator level control system is determined, its control performance is mainly related to the control parameters of the control system. In order to optimize the performance of the control system, it is necessary to adjust the corresponding control parameters of all controllers. Eventually, a set of parameter combinations is found that will optimize the performance of the steam generator level control system. A set of control parameter combinations that can optimize the performance of the control system is defined as the optimal parameter combination solution. The performance optimization problem is converted into the following mathematical expression:

$$\begin{aligned} &\max \ Perf = f(x) \\ &s.t. \ \ x \in \Omega \end{aligned} \tag{2}$$

Here, *Perf* represents the operating performance index of the control system, *x* represents the selected control parameters, Ω represents the selected range of parameters, and *f*(*x*) represents the functional relationship between the control parameters and their corresponding control system performance indexes.

In the context of multidimensional, noisy environments, the model-free gradient approximation optimization method is a good choice, with SPSA algorithm being one of them [7]. However, SPSA still has some issues, such as requiring a certain amount of experimentation and being occasionally imprecise. Therefore, prior knowledge can be introduced to optimize the gradient estimation algorithm, reducing experimental costs, ultimately leading to the proposal of a multi-source hybrid data-driven optimization method based on model accuracy gradient estimation (MHDO-MAGE).

The structure of the multi-source hybrid data-driven optimization method based on model accuracy gradient estimation (MHDO-MAGE) is shown in Figure 3.

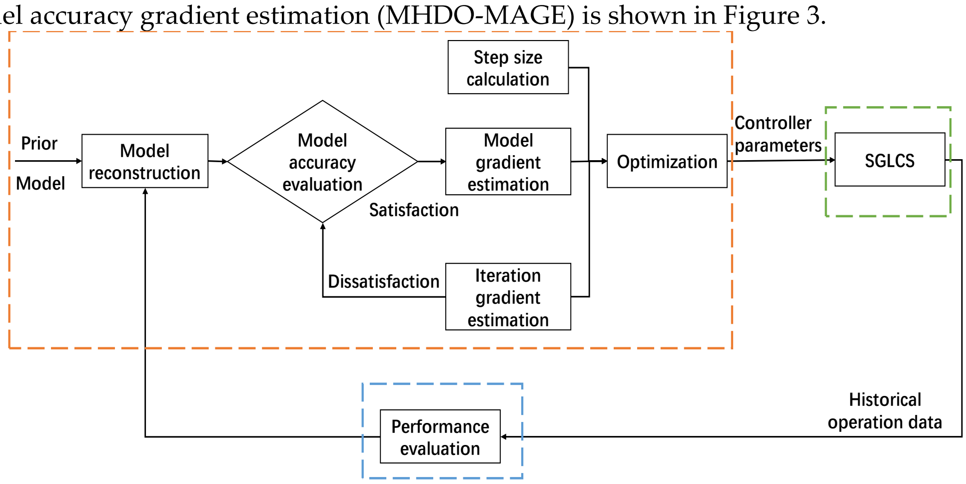

Figure 3. The structure of MHDO-MAGE

3. Simulation and result analysis.

3.1. Experimental parameter setting

Once the structure of the SGLCS is determined, its control performance is only related to the control parameters. In order to achieve the optimal control performance of the SGLCS, a set of optimal parameter combinations must be found, which is the process of system performance optimization [8]. As shown in Figure 2, the SGLCS adopts a three-pulse cascade PID control scheme for 100 % FP (the operating power of the SG is at Full load Power), 50 % FP, and 15 % FP. A total of six controller parameters for the main and secondary PIDs are selected as the optimization variables, which are denoted as $X = [X_1, X_2, X_3, X_4, X_5, X_6]^T$. The maximum number of iterations is set to 20. The details and constraints of the optimization variables are described in Table 1, and the system parameters are set according to Table 2.

Table 1. Controller parameters and constraint range Settings.

Variable NO.	**Variable description**	**Constraint rang**		
		100 %FP	50 %FP	15 %FP
X_1	Master controller	[0 0.6]	[0.09 0.17]	[0.01 0.04]
X_2		[0 0.0035]	[5.44 20] $\times 10^{-4}$	[3.26 3.86] $\times 10^{-6}$
X_3		[-1 3.2]	[0.08 1.8]	[-0.044 1.29]
X_4	Secondary controller	[0 2.2]	[0 2.2]	[0 2.2]
X_5		[0 1.2]	[0 1.2]	[0 1.2]
X_6		[0 1.2]	[0 1.2]	[0 1.2]

Table 2. Cascade PID control system parameter setting.

Variable number	**Variable description**	**Set point**
Lv-sp	Horizontal target set value	0 (mm)
tau	Feed water valve adjustment	0.05
disturb	Perturbation ratio	5 %
td	Disturbance setting time	100 (s)
total	Total simulation duration	1200 (s)

Without loss of generality, under the constraints of Table 1, the Monte Carlo method is used to randomly select an initial point $X_0 = [0.077,\ 3\text{e-}04, 0.2, 1, 0.5, 0]^T$ as the controller parameter. Different initial points are used in the iterative experiments, and the specific parameters are shown in Table 3. The optimization parameter constraints refer to Table 1, and the effectiveness of the MHDO-MAGE algorithm is verified under a maximum of 20 iterations.

Table 3. Initial controller parameter Settings at different power levels.

Power	**Initial parameter**
15 %FP	$x_0 = [0.03,\ 3.55\times10^{-6},\ -0.21,\ 0.6,\ 0.43,\ 0.62]^T$
	$x_0 = [0.03,\ 3.26\times10^{-6},\ -0.21,\ 0.9,\ 0.1,\ 0.12]^T$
50 %FP	$x_0 = [0.1,\ 0.0003,\ 0.02,\ 1.36,\ 0.4,\ 0.02]^T$
	$x_0 = [0.15,\ 0.00025,\ 0.02,\ 0.36,\ 0.43,\ 0.62]^T$
100 %FP	$x_0 = [0.3,\ 1.8\times10^{-3},\ 1.1,\ 0.4,\ 0.5,\ 0.9]^T$
	$x_0 = [0.1,\ 3.1\times10^{-3},\ 0.1,\ 1,\ 0.9,\ 0.9]^T$

3.2. Validation of effectiveness

MHDO-MAGE is an optimization algorithm based on a hybrid of prior models and online experiments. It does not change the basic framework of the SPSA algorithm, and its convergence is consistent with the SPSA method. The effectiveness of this random search algorithm is verified through experimental design and numerical statistical analysis. In this study, the system performance indicator of ITAE is analyzed to examine the change of model accuracy at 90%, 80%, 70%, and 60% power levels.

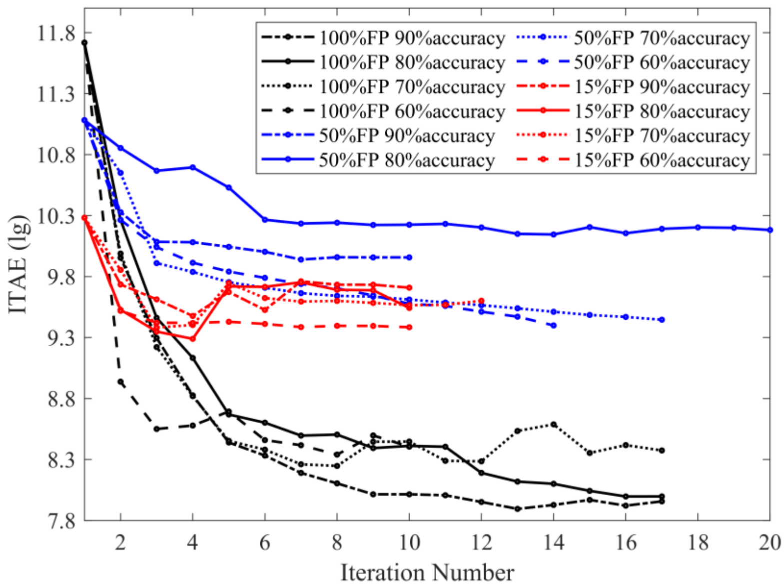

Figure 4. Comparison of Iteration Points for Different Power Levels and Model Accuracies.

As shown in Figure 4, for the same initial point, with increasing iterations, the overall trend of ITAE is decreasing, indicating a significant improvement in the performance of the control system under different power levels and model accuracies. This proves the effectiveness of MHDO-MAGE in optimizing system performance. Due to the addition of intelligent termination criteria, the optimization process requires only about 14 iterations, which is less than the maximum number of iterations of 20. This indicates that MHDO-MAGE can achieve the optimization goal in a limited amount of time, reduce the number of iterations, and significantly reduce the optimization cost.

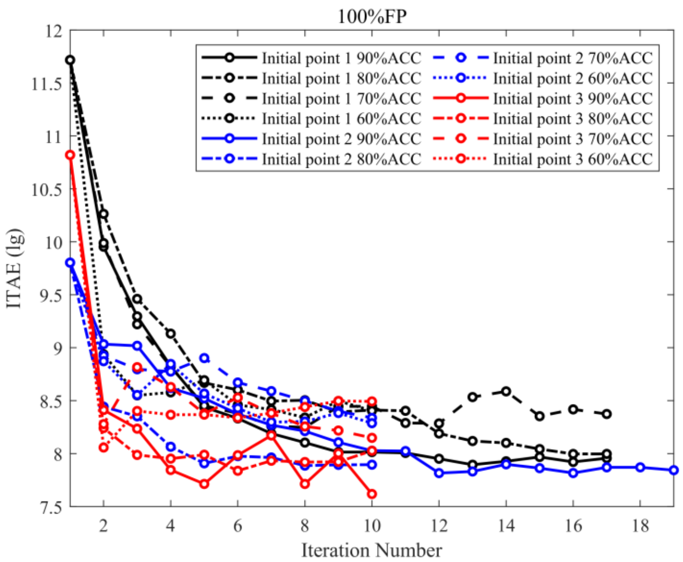

Figure 5. (a)

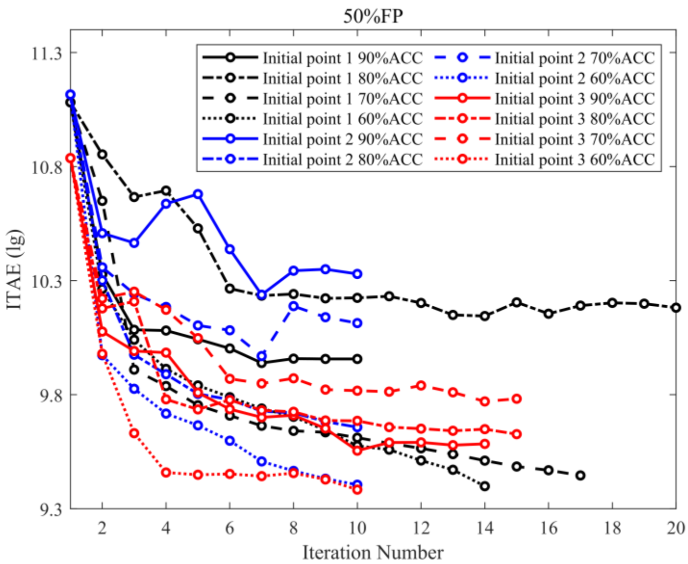

Figure 5. (b)

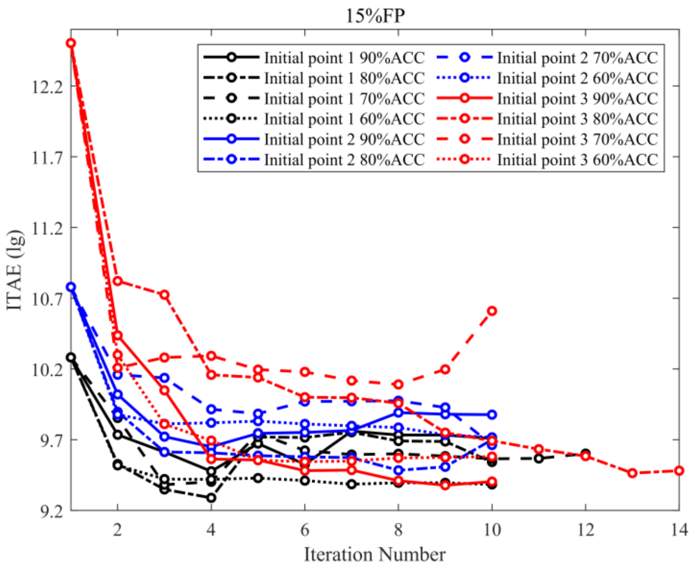

Figure 5. (c)

Figure 5. the iteration comparison of different model accuracies for different initial points and power levels: (a) iteration comparison of different accuracies for different initial points under 100% power; (b) iteration comparison of different accuracies for different initial points under 50% power; (c) iteration comparison of different accuracies for different initial points under 15% power.

Figure 5 shows the iterative changes of system performance optimization index ITAE at different initial points of different model accuracy under three different powers.

First of all, at different initial points with different power and different model accuracy, ITAE on the whole showed a downward trend with the increase of iteration times, so the performance of the control system was improved. Secondly, the optimization experiments of three different initial points all achieved similar optimization processes, which proved the effectiveness of the optimization method on the performance optimization of different initial points within a limited number of iterations. Finally, it can be seen from the optimization curve that the selection of different initial points under different model accuracy presents a downward trend on the whole, but the effect is different, which indicates that the selection of initial points will have an impact on the optimization efficiency of system performance.

In summary, ITAE is related to power, model accuracy and initial point selection. ITAE values can be effectively reduced by selecting appropriate power, model accuracy and initial point, which further verifies the effectiveness of MHDO-MAGE method.

4. Conclusion

In this paper: a multi-source hybrid data driven optimization method based on model accuracy gradient estimation (MHDO-MAGE) is proposed based on E.Ving's three-impulse cascade PID liquid level control system model. This method takes the model accuracy after model reconstruction by prior model and iterative data as the judgment basis. When the model accuracy meets the set threshold, the model gradient estimation method is used. Otherwise, online gradient estimation is used. Simulation results show the effectiveness of the multi-source hybrid data driven method.

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