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Proceeding Paper

CG-SPSA Based Performance Optimization Strategy for the Steam Generation Water Level Control System of Nuclear Power Plant †

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Abstract: The Steam Generator Liquid Control System (SGLCS) is a crucial energy exchange equipment in nuclear power plants. However, the performance optimization of the system is hampered by issues such as time consumption, dependence on experience, and difficulty in attaining the optimal solution. In this paper, a new SPSA method, CG-SPSA, based on data-driven optimization and SPSA methods is proposed. The gradient approximation is achieved by using a restructured model with dynamic confidence levels. This method offers a unique fusion of the data-driven and model-driven approaches to optimization. Simulation experiments demonstrate that this method outperforms traditional SPSA in terms of optimization performance, leading to a significant improvement in optimizing system control performance.

Keywords: SGLCS; data driven; SPSA; dynamic confidence; model reconstruction

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1. Introduction

The steam generator (SG) in a high-temperature gas-cooled reactor (HTGR) nuclear power system is one of the most critical equipment, directly related to the stable and secure operation of the nuclear power plant [1]. Therefore, achieving stable liquid level in the SG within the preset range is of great significance for the normal operation of the nuclear power plant. The SG level control system typically adopts a fixed-parameter PID controller [2], and the most commonly used method currently is still the traditional PID control method [3]. However, they are plagued by outstanding issues such as time-consuming performance optimization, dependence on experience, and difficulty in achieving optimality. Not only that, but parameter adjustments in the program increase the number of iterations, leading to increased actual costs. Different from the traditional PID control SG level method, this paper proposes a performance optimization strategy for the nuclear power plant SG level control system based on a mixture of confidence levels (CG-SPSA), considering both control accuracy requirements and actual cost constraints. By setting prior models and online data confidence intervals, the PID control parameter adjustment time can be saved while meeting accuracy requirements, thus accelerating program execution and aiming to reduce optimization costs by reducing the number of iterations.

This paper presents a design analysis and principle explanation of the CG-SPSA optimization algorithm. In the context of the SG level control system in nuclear power plants, a simulation platform was built based on E. Irving's SG water level model [4]. A series of performance optimized test simulations were designed and conducted to verify the feasibility of the algorithm for real industrial process control systems.

2. Performance Optimization Strategy for SG Liquid Level Control Systems (SGLCS)

2.1. SGLCS

Typically, the SG level control system (SGLCS) adopts a three-impulse cascade PID control system [5], The automatic control system for three-impulse-feedwater is a control system composed of a water level as the primary controlled signal, steam flow as feedforward signal, and feedwater flow as inner-loop feedback control signal. As illustrated in Figure 1.

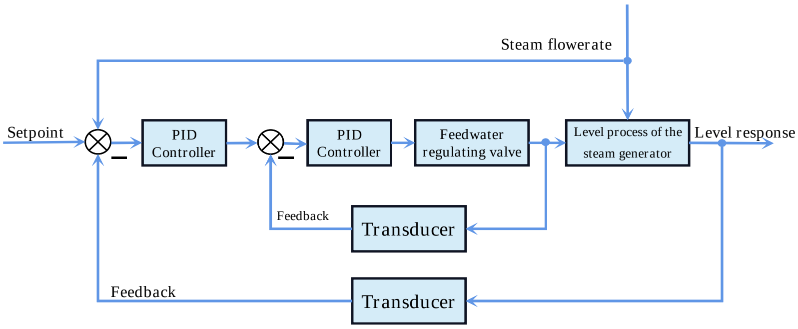

Figure 1. Structure of three-impulse cascade PID control system.

Once the structure of the SGLCS is determined, the control performance is mainly determined by the controller parameters of the control system. To optimize the performance of the control system, it is necessary to adjust the relevant parameters of each controller and find the optimal parameter combination to achieve the best performance of the SGLCS. This paper adopts the time integral multiplied by the absolute error index (ITAE) as the performance evaluation index of the control system to evaluate the characteristics of the step response transient curve [6], which is formulated as follows:

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

In this equation, e(t) represents the error signal, and Ts represents the simulation time.

A set of parameter combination schemes that can optimize the control performance of the relevant control system is defined as the optimal parameter combination scheme, expressed in mathematical language as follows:

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

Perf refers to the performance index of the control system. *x* represents the selected control parameters, and indicates the selected range of control parameters. *f(x)* represents the functional relationship between the controller parameters *x* and their corresponding control system performance index, *Perf*.

The traditional parameter optimization method of SG is to use the SPSA algorithm, which is a model-free optimization method, suitable for multidimensional and noisy environments [7]. As a stochastic approximation algorithm, SPSA still has problems in computing gradients, and in the case of large samples, due to statistical principles, although SPSA can be considered to take all directions into account when computing gradients from a macro perspective, it is not suitable for systems with high iteration costs. As SPSA requires experiments to be conducted at each iteration, although the data obtained from the experiment is accurate, the efficiency is low due to the fact that it can only consider the gradient of one direction at a time. Figure 2 below illustrates the principle of the traditional SPSA method:

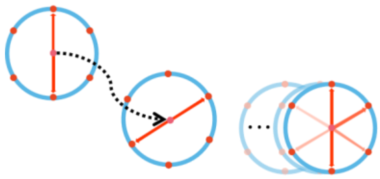

Figure 2. Simulation diagram of conventional SPSA optimized gradient estimation with large sample conditions.

This article proposes an optimization algorithm (CG-SPSA) based on the idea mentioned above. The algorithm employs precise analysis of the computational model for the calculation of the gradient obtained by the SPSA algorithm, and organically integrates it with prior model accuracy to achieve a dynamic confidence level gradient estimation SPSA optimization method.

The optimization strategy of the CG-SPSA algorithm based on mixed confidence level is illustrated in Figure 3.

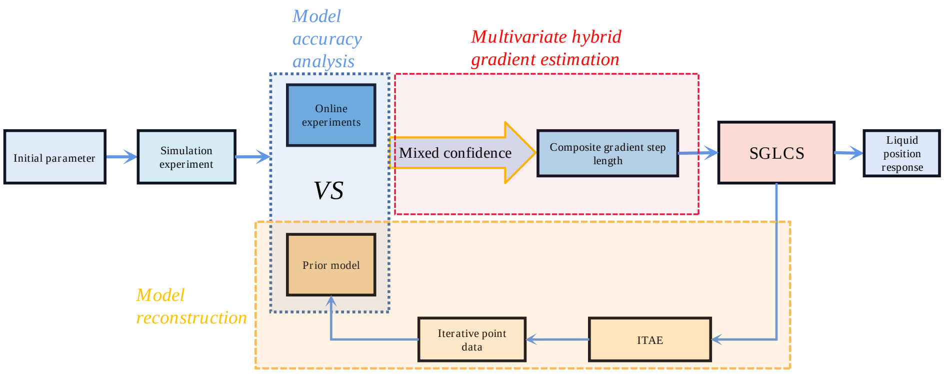

Figure 3. SGLCS Performance optimization strategy.

These are the specific steps of CG-SPSA, and the relevant flow chart is shown below in Figure 4.

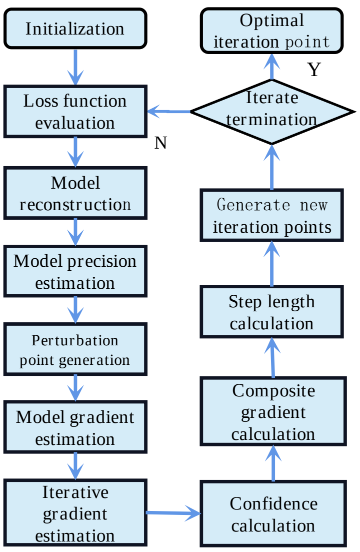

Figure 4. Flow chart of the CG-SPSA.

3. Simulation and Result Analysis

3.1. Experimental Parameter Setting

As shown in Figure 1, SGLCS adopts a three-impulse cascade PID control system, which includes a main PID and an auxiliary PID, for a total of six parameters. These parameters are treated as optimization variables, $X = [X_1, X_2, X_3, X_4, X_5, X_6]^T$. The maximum number of iterations is set to 20. The specific optimization variables and constraints under SG full power operation are shown in Table 1, while the system parameters are shown in Table 2.

Table 1. Controller parameters and the constraint range settings.

Variable NO.	Controller	Change Interval
X_1		[0 0.6]
X_2	principal controller	[0 0.0035]
X_3		[−1 3.2]
X_4		[0 2.2]
X_5	auxiliary controller	[0 1.2]
X_6		[0 1.2]

Table 2. Parameter settings of the control system.

Parameter Symbol	*Parameter Description*	*Set Value*
Lv_{sp}	Level target set value	0 (mm)
Tau	Adjustment value of feedwater valve	0.5
Disturb	Disturbance ratio	10%
t_d	Setting disturbance time	100 (s)
total	Total simulation duration	1200 (s)

To ensure the generality of the study, Monte Carlo method is used to randomly select the initial point $X_0=[0.077, 3\times10^{-4}, 0.2, 1, 0.5, 0]^T$ under the constraints shown in Table 1, and this point is used as the controller parameters. Next, the experiment was conducted on the simulation platform and optimized with CG-SPSA, and after the SGLCS full power operation, the optimal controller parameter is obtained as $X=[0.559, 3.5\times10^{-3}, -0.498, 2.2, 1.2, 0.335]^T$.

3.2. Results for Comparison and Analysis

3.2.1. Feasibility and High-Efficiency Performance Validation

The Figure 5 above shows the optimization trajectories of traditional SPSA, FDSA, and CG-SPSA optimization algorithms under different precisions. At the same time, the improved CG-PSPSA optimization curve is smoother and has a faster response time, indicating that the mixed confidence approach can make the gradient calculation more accurate and significantly improve the optimization efficiency.

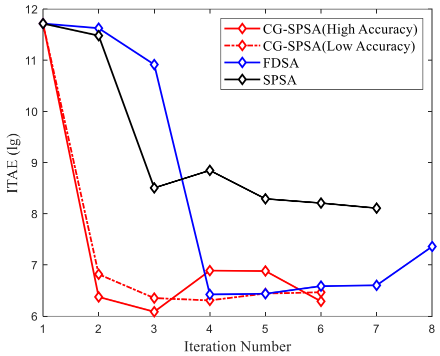

Figure 5. An iterative comparison plot between traditional SPSA, FDSA and improved CG-SPSA.

3.2.2. Optimization Performance Validation at Different Initial Points

As can be seen from the figure, optimization can be achieved for three random initial points, and the same effect can be achieved, resulting in the same optimal value. The experiments confirm that the optimization performance of the CG-SPSA algorithm is still effective for different initial parameters.

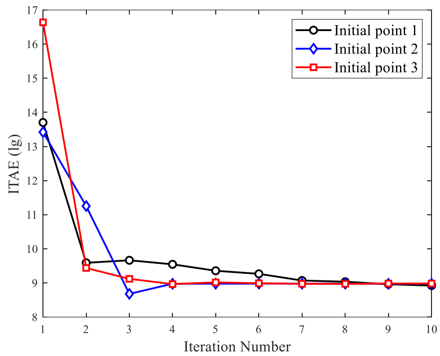

Figure 6. CG-SPSA optimized trajectories at different initial points.

3.2.3. Validation of Parameter Optimization

Figure 7 shows the optimization trajectory of CG-SPSA for parameters under different levels of precision. As can be seen from the figure, with the iteration, the controller parameters continue to change, indicating that the parameter optimization is proceeding.

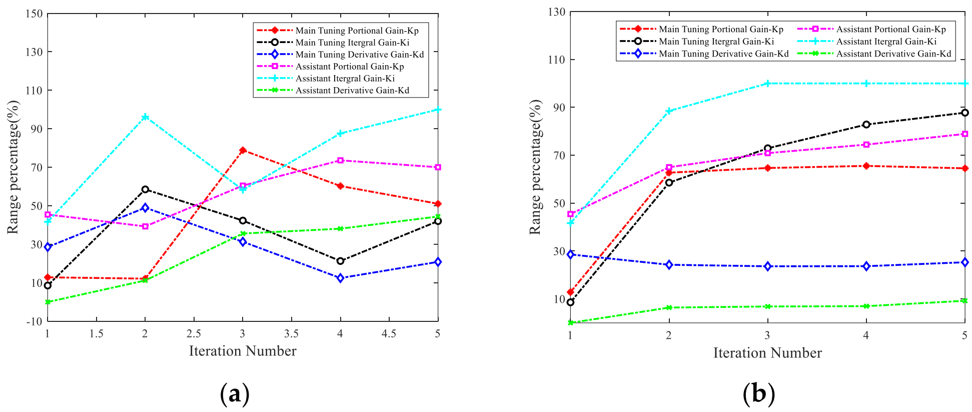

Figure 7. (**a**) High-precision parameter iteration trajectory; (**b**) Low-precision parameter iteration trajectory.

3.2.4. Output the Optimized Performance Validation

To analyze the optimization effect of CG-SPSA on the SG level control system output object, experiments were designed to investigate the effect of CG-SPSA under different levels of precision on the system's liquid level output. Figure 8 shows the liquid level response curves before and after optimization under different levels of precision.

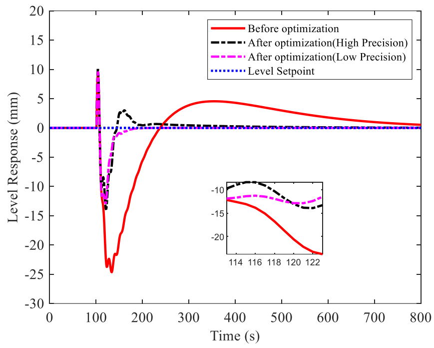

Figure 8. The liquid level comparison plots before and after optimization.

The figure above analyzes the liquid level comparison between before and after optimization of the SG system. The results show that CG-SPSA can optimize the liquid level response performance of the SG system. As the number of iterations increases, the optimization effect becomes more significant. The experiments confirm the effectiveness of the CG-SPSA optimization algorithm under the data-driven framework for achieving SG performance optimization.

4. Conclusions

Nuclear power plant steam generators have complex thermodynamic processes, and high demands for stable output liquid levels. In this paper, a steam generator level control system based on the data-driven framework and the dynamic confidence gradient estimation algorithm was studied, using E. Irving's classic steam generator level control system model.

The simulation experimental results show that designing the controller using a mixed confidence method has better control effectiveness than traditional control methods. The CG-SPSA optimization algorithm with mixed confidence has a significant effectiveness in achieving SG performance optimization, demonstrating the superiority and good engineering application value of the CG-SPSA algorithm.

Author Contributions:.

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Conflicts of Interest: The authors declare no conflict of interest.

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