

Risk Assessment, Optimization and Surrogate Modeling for the Water Level Control System

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Maintaining optimal water levels in pressurizers is crucial to ensuring the stable operation of nuclear reactor primary circuits. This paper presents an integrated framework for system risk analysis and operational strategy optimization in water level control systems. We first develop a comprehensive control system model and employ the dynamic event tree (DET) methodology to investigate the temporal evolution of system risk during extended operations. Then we develop a multi-objective optimization algorithm to identify optimal operational strategies that minimize long-term system risk while balancing safety requirements with operational efficiency. To address the computational challenges of state-space explosion inherent in long-sequence DET analysis, we propose a neural network-based surrogate model that enables rapid risk prediction while maintaining accuracy. Experimental results demonstrate that our approach achieves significant computational efficiency gains in risk prediction while providing actionable insights for risk-informed decision-making. The neural network surrogate model reduces the majority of the prediction time compared to conventional DET methods without compromising prediction accuracy. This research offers a practical solution for real-time risk assessment and optimal control in complex nuclear power systems, with potential applications in other safety-critical industrial domains.

Keywords: Dynamic Event Tree, Multi-objective Optimization, Neural Network Surrogate, Risk Assessment.

1. Introduction

In pressurized water reactors (PWRs), the pressurizer is a key component for primary-loop pressure regulation and thermal-hydraulic stability, and its operating condition is directly related to reactor cooling capability and overall system integrity. Deviation of the pressurizer water level from its design range may weaken the inherent pressure self-regulation capability, degrade primary-loop pressure control performance, and consequently threaten core thermal safety. Under operational transients, load-following conditions, and accident scenarios, the pressurizer water level is jointly influenced by control logic, valve and heater responses, and the timing of component failures, exhibiting pronounced dynamic evolution. However, in conventional Probabilistic Risk Assessment (PRA) for nuclear power plants,

water-level-related systems are typically analyzed using static event trees or fault tree methods, which neglect the temporal coupling between accident events and control actions. As a result, these approaches are inadequate for accurately representing dynamic processes with strong time-dependent behavior (Wiltbank and Camille 2021). To address these limitations, dynamic risk assessment methods—particularly the Dynamic Event Tree (DET) approach—have been proposed and progressively applied to nuclear system safety analysis. By coupling system dynamic models with discrete event branching, DET explicitly characterizes accident evolution paths and the probability distributions of terminal states along the time dimension. Nevertheless, DET-based analyses generally require a large number of simulations, resulting in high computational costs for parameter studies

and real-time decision-making. This situation has motivated increased interest in acceleration strategies and surrogate modeling techniques for efficient risk assessment.

Existing studies typically focus on either risk modeling, control optimization, or surrogate modeling separately. However, few works integrate dynamic risk analysis, intelligent control optimization, and machine-learning-based acceleration into a unified framework for nuclear system operation support. From a methodological perspective, this study integrates three classes of approaches: Dynamic event trees, multi-objective optimization, and deep-learning-based surrogate modeling.

With respect to dynamic event trees, previous studies have systematically compared different DET implementations in the context of nuclear accident analysis, clarifying their respective applicability and limitations (Karanki et al. 2018), and have successfully applied DET to representative transient scenarios such as station blackout accidents (Amirsoltani et al. 2022). Meanwhile, advances in time-dependent failure rate modeling and dynamic reliability analysis have provided a theoretical foundation for probability updating within the DET framework (Xu et al. 2019). Although DET analysis provides a powerful tool for modeling accident evolution in complex nuclear systems, its computational cost grows exponentially with simulation time due to the state explosion problem. This limitation makes it difficult to support rapid risk-informed operational decision making.

For control parameter optimization, Particle Swarm Optimization (PSO) (Kennedy and Russell 1995) and its multi-objective extension (MOPSO) (Yang et al. 2009) have been widely employed for engineering multi-objective optimization problems due to their simple structure and strong global search capability. Since their introduction, these algorithms have been applied to multi-parameter optimization of nuclear power plant simulation models (Li et al. 2025) as well as to optimization tasks in nuclear reactor radiation shielding design and related applications (Wu et al. 2021).

To address computational cost, surrogate models have been increasingly introduced into the field of probabilistic safety analysis in recent years as efficient replacements for high-fidelity

simulators, enabling accelerated risk evaluation (Navarro et al. 2026). Among these approaches, Transformer models based on self-attention mechanisms (Vaswani et al. 2017) have demonstrated significant advantages in long-term time-series modeling and high-dimensional parameter mapping. As a result, Transformers have shown superior performance compared with traditional recurrent neural networks (RNNs) and long short-term memory (LSTM) models in tasks such as predicting time-series data from key nuclear power plant sensors (Zhang et al. 2025) and forecasting the temporal evolution of critical parameters under loss-of-coolant accident (LOCA) conditions (Li et al. 2024).

Building on the aforementioned research foundations, this study aims to simulate pressurizer water level control by constructing a dynamic event tree model of the water level control system. The DET approach is used to perform high-fidelity risk calculations of water level evolution and associated risk metrics under fault conditions. Subsequently, Particle Swarm Optimization is applied to optimize control parameters such as valve actuation speeds and alarm threshold settings, with the objectives of minimizing system risk while maximizing the probability of regular operation. Finally, a Transformer-based surrogate prediction model is developed to enable rapid forecasting of dynamic risk evolution under different control strategies.

The main contributions of this study are summarized as follows:

- An integrated risk-informed decision framework is proposed for water level control systems, combining dynamic event tree modeling, multi-objective optimization, and machine learning.
- A multi-objective optimization strategy is developed to optimize control parameters considering both system risk and availability.
- A Transformer-based surrogate model is constructed to rapidly predict the dynamic risk evolution, significantly reducing the computational cost compared with traditional event tree simulations.

The proposed framework enables fast risk-informed operational decision making for safety-critical nuclear systems.

2. System Modeling and Risk Quantification

The system investigated in this study is a water level control system whose configuration comprises a water tank, on-off valves and their associated signal receivers, water injection and discharge pipelines, and water level sensors.

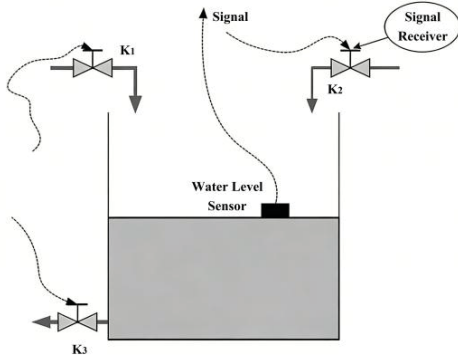


Fig. 1. Schematic diagram of the water level control system

The initial system water level is defined as zero. When the water level deviation remains within ± 3 m of the normal level, the system is considered to be operating under normal conditions and able to maintain its safety function; otherwise, it is considered failed. To maintain water level stability, the adopted control strategy is as follows. When the water level deviation exceeds the ± 1 m alarm threshold from the initial level, the water level control valves are activated. If the water level falls below -1 m, the injection valves K1 and K2 are opened while the discharge valve K3 is closed; if the water level rises above 1 m, valves K1 and K2 are closed and valve K3 is opened, unless the signal receiver associated with the corresponding valve has already failed. The injection rates of valves K1 and K2 are 1.0 m/h and 0.5 m/h, respectively, while the discharge rate of valve K3 is -1.2 m/h.

In addition to the control strategy, the dynamic event tree model discretizes the accident progression into branches to simulate water level evolution under different fault scenarios. The signal receivers associated with each valve are assumed to have identical and constant failure rates. In the discrete dynamic event tree simulation, this implies that, within each one-hour interval, each signal receiver has a fixed probability of failure, and simultaneous failures of

multiple signal receivers are not considered. Failure of a signal receiver causes the corresponding valve state to reverse and become locked, indicating the loss of control functionality for that valve.

The dynamic event tree is expanded in a time-stepping manner. At each time step, the occurrence or non-occurrence of failure events for each signal receiver generates new branches. System state variables evolve along each branch according to the applicable control strategy and are propagated to the next time step until the prescribed simulation end time is reached or the system water level deviates by more than ± 3 m from the normal range, which is defined as system failure. The system state variables include the water level (W), initially set to 0 ; the valve states (V), with initial values of $K1$, $K2$, and $K3$ equal to 1 , 0 , and 1 , respectively, indicating that $K1$ and $K3$ are open while $K2$ is closed; the signal receiver failure states (F), initially set to 0 , 0 , and 0 ; and the branch probability (P), initially equal to 1.0 .

By applying the discrete dynamic event tree approach to system-state analysis, all possible system states at any given time can be enumerated, and the system risk over a specified operating duration can be predicted. In the following, Case 1 is analyzed by setting the failure rate of the signal receivers associated with the valves to 0.01 h^{-1} and adopting a time step of one hour. The event tree constructed for the first three steps is illustrated in Fig. 2.

Taking the branch corresponding to the failure of K1 followed by the failure of K2 as an example, at time 0 , the failure of K1 causes its state to reverse and become locked, resulting in the valve state vector (V) changing to $[0, 0, 1]$. Consequently, during the interval from 0 to 1 h, only the discharge valve K3 remains active, and the system water level decreases from 0 to -1.2 m. At time 1 h, the failure of K2 leads to another state reversal and locking. In addition, because the system water level is below the alarm threshold, the control strategy is adjusted by closing valve K3, while valves K1 and K2 remain locked due to failure. As a result, the valve state changes to $[0, 1, 0]$. During the interval from 1 to 2 h, only the injection valve K2 is active, and the water level increases from -1.2 m to -0.7 m.

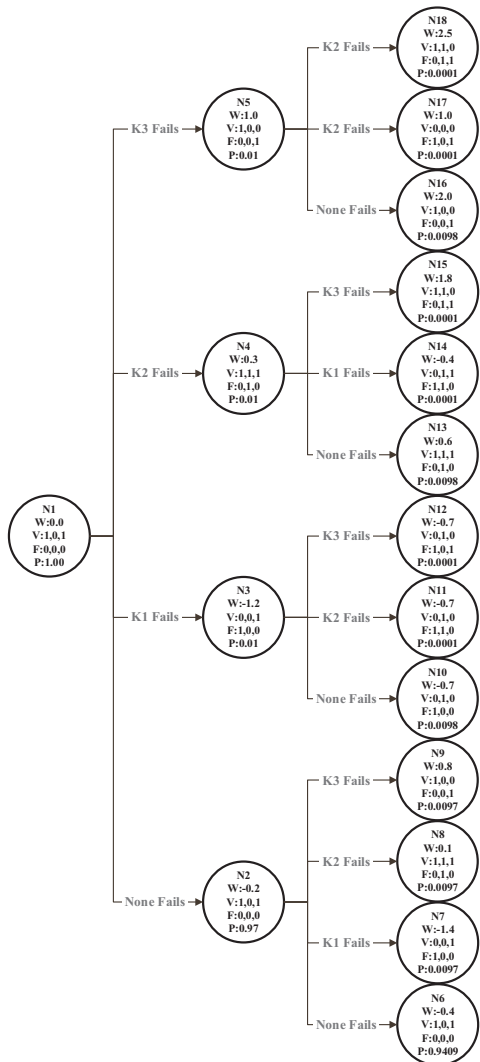


Fig. 2. Event tree for Case 1(first three steps)

To assess the system's reliability during long-term operation, a discrete dynamic event tree is employed to evaluate system risk over extended operating durations. In terms of risk metrics, the probability-weighted average water level is a comprehensive safety measure that weights water levels at each time step by the corresponding branch probabilities. This metric reflects the overall effectiveness of water level control during long-term operation. In addition, the probability that the water level remains within the normal

operating range is calculated to characterize the overall system risk over prolonged operation.

Through dynamic event tree simulations, trajectories of water level evolution under different combinations of component failures can be obtained, from which the aforementioned risk metric time series are derived. Fig. 3 presents the reliability analysis results for Case 1 over a 50-hour operating period.

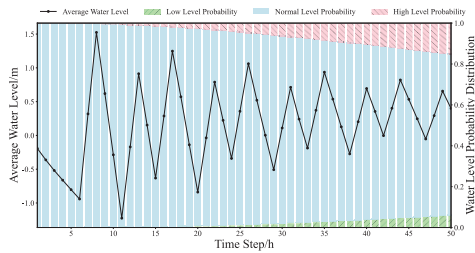


Fig. 3. Reliability analysis results for Case 1

It can be observed that, as time progresses, the expected average water level exhibits a fluctuating upward trend, reaching approximately 0.40 m at 50 h. Meanwhile, the probability of the system deviating from the normal water level range (i.e., high- and low-water-level conditions) gradually increases. This result indicates that, with increasing operating time, the risk of signal receiver failure accumulates, leading to a degradation and eventual loss of water level control capability.

To investigate the impact of different signal receiver failure rates on system risk, additional studies were conducted for Case 0 and Cases 2-5, in which the signal receiver failure rates were set to 0 and 0.02-0.05 h⁻¹, respectively. Table 1 presents a comparative analysis of the system risk at 50 h under different signal receiver failure rates.

Table 1. System risk at 50 hours		
Case Number	Average Level (m)	Normal Level Probability
0	0.00	1.0000
1	0.40	0.7895
2	0.69	0.5080
3	0.82	0.3104
4	0.88	0.1898
5	0.90	0.1190

As the signal receiver failure rate increases, the system’s average water level rises continuously, while the probability of maintaining a normal water level decreases, indicating a steady increase in overall system risk. Without modifying the component failure rates, it is therefore necessary to make intelligent decisions about operating strategies to identify suitable control schemes that can reduce the average water level while simultaneously increasing the probability of normal operation.

3. Multi-Objective Optimization

For the water level control system, Case 4 is selected as the computational scenario for optimization, with a runtime of 50 hours. The key parameters to be optimized simultaneously consider the system’s physical constraints and safety requirements, including: the flow rates of valves K1, K2, and K3, and the control strategy, namely the adjustment of alarm thresholds.

Table 2. Key parameters to be optimized

Parameter	Original Value	Range
K1 rate (m/h)	1.0	[0.8, 1.2]
K2 rate (m/h)	0.5	[0.4, 0.6]
K3 rate (m/h)	-1.2	[-1.4, -1.0]
Low alarm threshold (m)	-1.0	[-1.2, -0.8]
High alarm threshold(m)	+1.0	[0.8, 1.2]

The constraint conditions are $K1 < |K3|$, $K1 + K2 > |K3|$

The optimization objective is to reduce the overall risk of long-term system operation while improving the water level control performance. Specifically, over a runtime of 50 hours, the absolute value of the average water level (obj1) should be as close as possible to the original water level (0), the smaller the better, while the probability of maintaining a normal water level (obj2) should be maximized, the larger the better. This constitutes a multi-objective optimization problem, in which a balance between risk and availability must be achieved under a set of feasible parameters.

The Particle Swarm Optimization (PSO) algorithm is a heuristic search method based on swarm intelligence, proposed by Kennedy et al. (1995). The algorithm initializes a swarm of

particles randomly distributed in the search space and iteratively updates their velocities and positions based on each particle’s personal best position and the global best position to search for the optimal solution. For multi-objective problems, a Multi-Objective PSO (MOPSO) approach can be used, introducing a Pareto dominance strategy to maintain a set of non-dominated solutions. Its simple structure and fast convergence make it advantageous for solving multi-objective optimization problems.

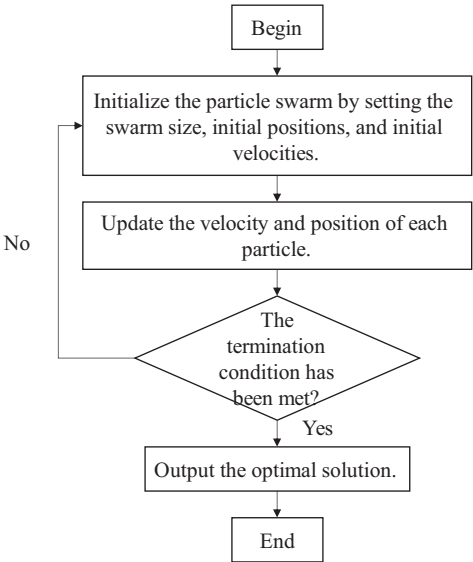


Fig. 4. Flowchart of the PSO

In this study, each particle represents a set of control parameter settings. During the optimization process, dynamic event tree simulations are performed for each particle’s parameter combination, and the corresponding risk indicators and normal level probabilities are used as objective function values. The particle swarm iteratively updates based on the fitness function (which integrates accident risk and normal level probability) and eventually converges to the Pareto-optimal solution set. The experimental setup includes an appropriate number of particles, iterations, and parameter boundary conditions. The fitness function in this study is defined as follows:

$$fitness=0.2\times obj1+0.8\times(1-obj2) \tag{1}$$

The optimized operational strategy obtained after applying the PSO algorithm for intelligent decision-making is as follows:

Table 3. Optimization results

Parameter	Original Value	Optimized Value
K1 rate (m/h)	1.0	0.8605
K2 rate (m/h)	0.5	0.4332
K3 rate (m/h)	-1.2	-1.2900
Low alarm threshold (m)	-1.0	-1.1540
High alarm threshold(m)	+1.0	1.0150

Fig. 5 and Fig. 6 compare the system's average water level and the probability of the normal level before and after optimization. The optimized operational strategy significantly reduces the predicted average water level over a 50-hour runtime (from 0.88 m to 1.94×10^{-4} m) and increases the probability of the normal level (from 0.1898 to 0.2148).

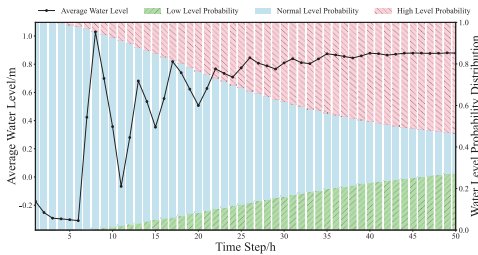


Fig. 5. Reliability analysis results for the original operational scheme

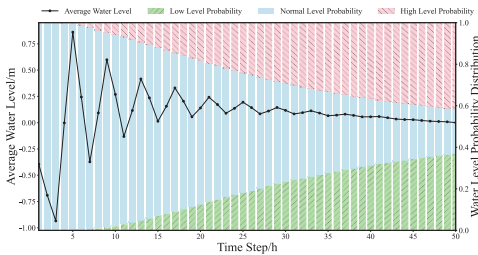


Fig. 6. Operational scheme after optimization by the intelligent decision-making algorithm

4. Transformer Surrogate Model

Although discrete dynamic event trees can accurately predict system risk over a specific period,

the state explosion caused by system branching leads to an exponential increase in computational time with the number of time steps during long-term predictions, making rapid risk calculations impractical. To accelerate the risk assessment process, a Transformer surrogate model is constructed to replace the time-consuming numerical simulations. The advantage of Transformers among neural network methods lies in their self-attention mechanism, which can effectively capture long-term dependencies, as well as their high parallel computing efficiency. First, a training dataset is generated by sampling the control parameter space using the event tree method: A large number of parameter combinations are randomly selected, and dynamic event tree simulations are run to obtain the corresponding risk indicators. The dataset is then split into training, validation, and test sets at 70:15:15. Next, a Transformer architecture is designed for modeling, with the control parameter vector as the input and the predicted risk indicators as the output. The Transformer model employs a multi-head self-attention mechanism that captures global coupling among input parameters, making it suitable for sequence-to-sequence mapping tasks. During training, the mean squared error (MSE) is used as the loss function, and model parameters are iteratively updated. Finally, the model is evaluated on the test set, and the results indicate that the Transformer surrogate model performs well at risk prediction.

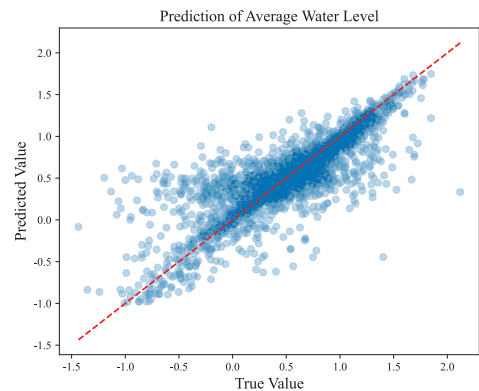


Fig. 7. Prediction of average water level on the test set

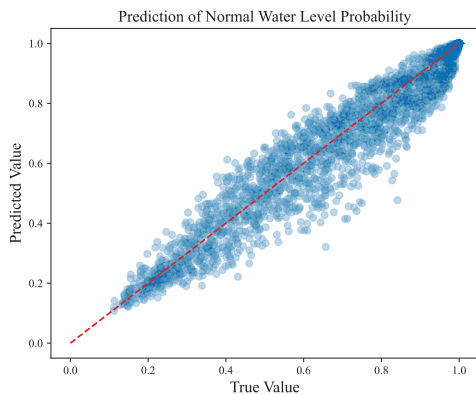


Fig. 8. Prediction of normal water level probability on the test set

In a new verification case, given a specific control strategy, the Transformer can accurately predict the system’s dynamic water level response and associated risk indicators. Since model inference requires only a single forward pass, its prediction speed is much faster than that of event tree simulations, enabling real-time risk assessment. Fig.9 and Fig.10 below compare the predictions of the Transformer with the results from the dynamic event tree model.

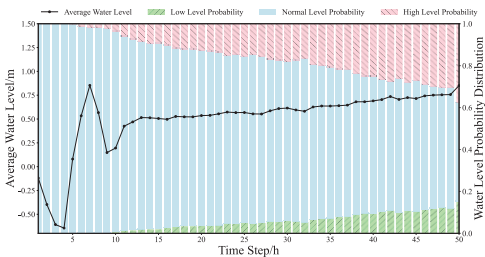


Fig. 9. DET model reliability analysis results

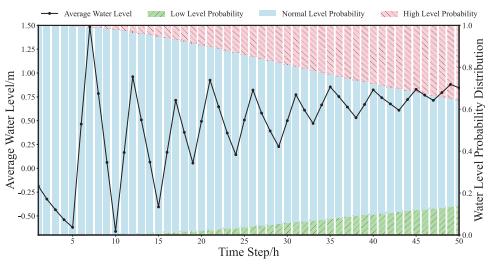


Fig. 10. Transformer model reliability analysis results

In the aforementioned case, the parameter combination is as follows: valve flow rates K1, K2, and K3 are 0.9 m/h, 0.55 m/h, and -1.1 m/h, respectively; signal receiver failure rate is 0.02/h; alarm water levels are 0.9 m and -0.9 m; prediction duration is 50 hours.

Table 4. Comparison of reliability analysis results

Parameter	DET Model	Transformer Model	Relative Error
Average Level (m)	0.85000	0.85112	0.13%
Normal Level Probability	0.50598	0.47198	-6.72%

It can be seen that the developed Transformer accurately predicts the normal-level probability and the absolute value of the average water level over the temporal sequence, especially at later time points. However, for short-term variations in the system’s average water level, the Transformer’s simulation performance is moderate. Therefore, further research will focus on enhancing the Transformer model’s ability to capture local features.

Meanwhile, compared with the original dynamic event tree simulation, the Transformer surrogate model reduces the prediction time from 49.5 s to 5.4 s under the same computational resources. This significant improvement indicates that the proposed approach can support near real-time risk evaluation. This capability is particularly important for nuclear power plant operation, where rapid assessment of control strategies is required during abnormal conditions.

Thus, the Transformer-based rapid prediction algorithm established in this study effectively enhances the efficiency of risk quantification and can provide technical support for quickly formulating risk mitigation strategies during nuclear power plant operations.

5. Conclusion

This study addresses safety issues in nuclear power plant water level control systems and proposes an integrated risk assessment and control strategy optimization method based on DETs. The proposed framework demonstrates that integrating dynamic risk assessment, intelligent optimization, and machine learning can provide an effective

tool for fast risk-informed decision support in nuclear power plant operation.

First, a dynamic event tree model of the system was established, modeling the core state variables and control logic, and defining risk indicators, such as the weighted average water level and the probability of the normal level, to quantify accident progression. Next, a multi-objective particle swarm optimization algorithm was employed to optimize the control parameters, aiming to reduce accident risk and improve system availability simultaneously. Experimental results show that the optimized strategy significantly enhances system safety performance. Finally, a Transformer surrogate model was trained using high-fidelity simulation data to enable rapid prediction of the complex water level–risk relationship, significantly improving assessment efficiency. The advantage of this approach lies in the organic integration of dynamic risk analysis with optimization and machine learning, enabling both accurate and fast risk assessment.

Several improvements can be pursued in future research. For the dynamic event tree model, Monte Carlo Discrete Event Tree (MCDET) methods and Monte Carlo sampling of failure rates can improve computational efficiency. For the surrogate model, methods to improve its ability to capture local features will be investigated to enhance water level prediction during intermediate stages. Additionally, further research will focus on coupling the surrogate model with multi-objective optimization algorithms to enable rapid multi-objective decision-making on system parameters, thereby improving the efficiency of multi-objective optimization.

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