Multi-Objective Bayesian Target Interval Optimization for Semiconductor Process Parameters

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***Abstract*—Semiconductor manufacturing is becoming increasingly complex, making optimization of process parameters both challenging and costly. In Physical Vapor Deposition (PVD) processes, high-dimensional nonlinear relationships between input parameters and output performance exacerbate these difficulties, particularly under conditions of limited data and multi-objective constraints. To tackle these challenges, we propose a Bayesian Optimization (BO) framework integrating Sparse Multi-task Gaussian Process (SMTGP) and Probability-guided Interval Search Mechanism (PRISM) for process parameter optimization. By incorporating a Multi-input Multi-output (MIMO) Predictor with Soft Physical Constraints, the framework effectively combines physical priors with learning-based modeling, enhancing predictive accuracy and reliability in low-data scenarios. Experimental evaluations across various scenarios demonstrate that the proposed method outperforms Random Search (RS) and classical BO in both efficiency and reliability.**

***Index Terms*—Bayesian Optimization, Target Interval Optimization, Multi-objective Optimization, Sparse Multi-task Gaussian Process, Semiconductor Process, Process Parameter Tuning**

I. Introduction

Semiconductor manufacturing serves as the foundation for modern electronic devices, driving advances in various industries. According to SEMI's forecast, the global semiconductor manufacturing equipment market is expected to reach a record high of $121 billion in 2025 [1]. As the backbone of chip fabrication, semiconductor equipment spans multiple stages, including wafer fabrication (e.g., etching, lithography, and deposition), packaging, and testing. As semiconductor devices scale to sub-3 nm nodes, manufacturing must meet increasingly stringent demands for precision, efficiency, and reliability. The complex physical and chemical interactions in semiconductor fabrication challenge manual decision-making, highlighting the demand for intelligent optimization techniques.

Among key fabrication steps, thin film deposition, especially Physical Vapor Deposition (PVD), is vital for achieving precise and uniform films that directly impact device performance and reliability. Optimizing PVD process parameters remains difficult due to complex variable interactions and the stochastic nature of deposition. Traditional methods like trial-and-error or physics-based modeling demand costly and time-consuming experiments. Meanwhile, as material requirements become stricter, achieving a balance among multiple performance objectives becomes increasingly challenging.

Each adjustment of the PVD process parameters is costly and requires substantial effort, leading to prolonged development cycles. Moreover, optimized configurations must meet multiple performance criteria within target ranges. The high cost and scarcity of data further limit the effectiveness of conventional optimization methods [2]. Recent advances in artificial intelligence (AI) have shown promise in reducing development costs and improving efficiency [3], making AI-driven optimization an attractive approach.

Several recent approaches in black-box optimization have been proposed to address high-cost, high-dimensional problems. For instance, Krishnamoorthy et al. [4] proposed diffusion models for black-box optimization, demonstrating the ability of diffusion models to explore high-value regions with minimal evaluations. Saad et al. [5] introduced a hybrid Kriging–Bat algorithm, leveraging surrogate modeling to reduce costs. Additionally, Li et al. [6] developed B2Opt, which prioritizes promising search regions to improve efficiency under strict data constraints.

Existing methods often target single-objective settings or demand heavy computation, limiting their practicality for PVD application. To address these challenges, we propose a Multi-Objective Bayesian Target Interval Optimization framework designed to guide PVD process parameters towards meeting multi-objective target constraints. The core motivation behind this framework is to minimize the number of costly experiments while ensuring that deposition outcomes remain within specified target intervals. To achieve this, we develop a Multi-input Multi-output (MIMO) Predictor with Soft Physical Constraints, which incorporates known physical constraints to enhance predictive precision under limited data conditions. This predictor effectively captures the intricate relationships between input variables and output performance metrics. Furthermore, we integrate a Bayesian Optimization (BO) strategy that leverages Sparse Multi-task Gaussian Process (SMTGP) to model correlations among multiple outputs, while Probability-guided Interval Search Mechanism (PRISM) evaluates the probability of meeting target interval constraints, and selects promising input candidates. Together, these components form

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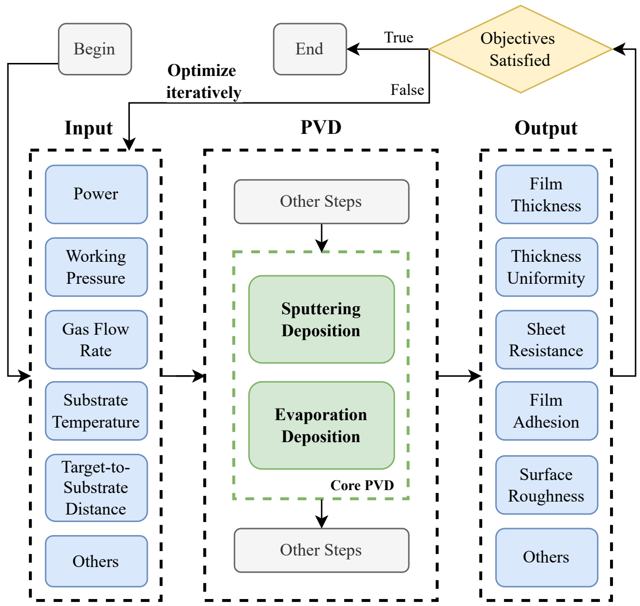

Fig. 1 PVD Workflow and Key Process Parameters

an efficient and constraint-aware optimization framework that reduces experimental costs and improves precision, even under limited data conditions.

The main contributions are summarized as follows:

- Problem Definition: Formulate PVD parameter tuning as a multi-objective interval optimization problem.
- Predictor Modeling: Propose a predictor with soft physical constraints to enhance accuracy with limited data.
- Optimization Framework: Integrate SMTGP and PRISM into BO to guide exploration and reduce costs.
- Experimental Validation: Demonstrate superior performance over baselines on simulated and benchmark-inspired datasets.

II. Preliminaries

A. Fundamentals of PVD in Semiconductor Fabrication

Recent advancements in semiconductor fabrication necessitate higher precision and efficiency. Among various fabrication techniques, PVD is extensively utilized for depositing functional thin films, playing a crucial role in forming metal interconnects, diffusion barrier layers, and electrodes [7]. The quality of PVD deposition, characterized by film thickness and uniformity, is strongly influenced by process parameters such as temperature, pressure, and power.

PVD operates by physically transferring material onto a substrate without chemical reactions, primarily through:

- Sputtering Deposition: Plasma bombardment ejects target atoms that condense on the wafer.
- Evaporation Deposition: Thermal energy vaporizes the target material, which then condenses on the substrate.

Optimizing the PVD process requires adjustments to key parameters based on experimental feedback or modeling to achieve the desired film characteristics. As illustrated in Fig. 1,

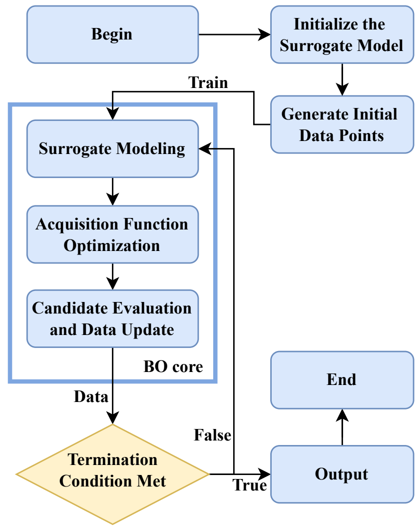

Fig. 2 Typical Workflow of BO

the optimization process continues until predefined objectives are met. The optimization of PVD process parameters encounters several challenges:

- High Experimental Costs and Data Scarcity: Each experiment requires a high-vacuum environment and precise calibration, making adjustments costly and leading to scarce experimental data.
- Multi-Objective Trade-offs: Multiple performance metrics exhibit nonlinear interactions. For example, increasing deposition power boosts the deposition rate but may degrade uniformity [7].
- Irreversible Deposition Process: PVD is inherently irreversible, leading to material waste and additional processing steps.

Unlike conventional methods that seek a single optimum, PVD optimization must balance multiple objectives within target intervals, thus demanding efficient strategies that reduce experiments while ensuring deposition quality.

B. Bayesian Optimization (BO)

BO is a probabilistic global optimization framework, especially effective for costly black-box functions [8], [9]. It models the objective function using a probabilistic surrogate, typically Gaussian Process Regression (GPR), and selects new evaluation points through an acquisition function, which balances exploration and exploitation [10]. This makes BO particularly suitable for PVD parameter optimization, where data is scarce and experiments are expensive. The optimization procedure in BO can be expressed as:

$$\mathbf{x}_{t+1} = \arg\max_{\mathbf{x}\in\mathcal{X}} \alpha(\mathbf{x} \mid \mathcal{D}_t), \tag{1}$$

where $\mathbf{x}$ represents the input space of process parameters, $\alpha(\mathbf{x} \mid \mathcal{D}_t)$ is the acquisition function conditioned on the observed dataset $\mathcal{D}_t$, and $\mathbf{x}_{t+1}$ is the next input to be evaluated. This iterative process is illustrated in Fig. 2.

However, standard BO methods often struggle with computational complexity and limited scalability, especially in

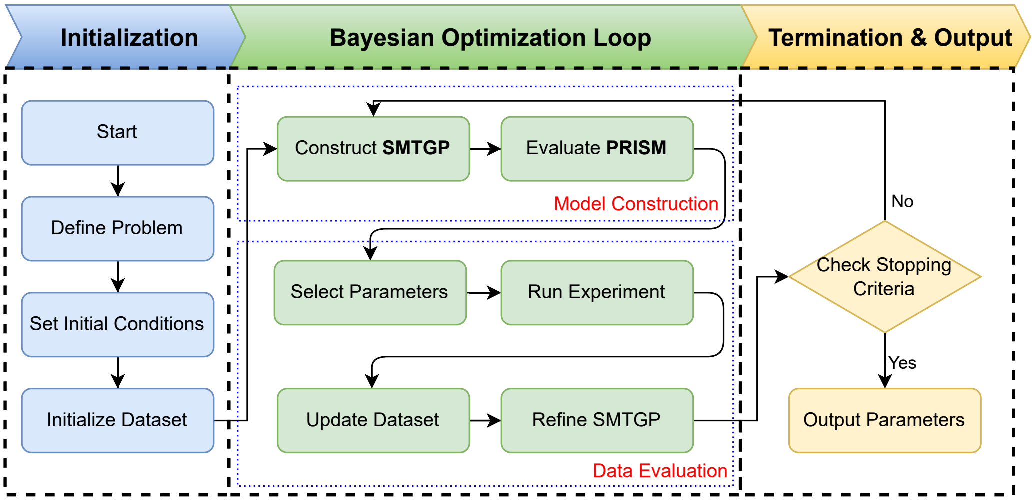

Fig. 3 Enhanced BO Framework for Target Interval PVD Parameter Tuning

high-dimensional or multi-objective settings [11]. In addition, traditional GPR models do not capture dependencies among multiple objectives, and common acquisition functions are not tailored for optimization over target intervals. These limitations motivate the development of more specialized BO frameworks, which we describe in Section III.

C. Sparse Multi-Task Gaussian Process (SMTGP) for Multi-Objective Optimization

Traditional Gaussian Processes (GPs) incur a computational complexity of $\mathcal{O}(N^3)$ when handling large datasets [12], where N represents the number of observed data points, increasing with each iteration of BO. In multi-objective settings, this complexity scales up to $\mathcal{O}(N^3M^3)$, where M is the number of objectives, due to the need for modeling cross-objective covariance structures. To address these challenges, surrogate models capable of capturing task-level correlations while maintaining computational efficiency have been proposed. Among them, SMTGP approximate full GP inference using a reduced set of inducing points $P \ll N$, reducing complexity to $\mathcal{O}(P^3M^3)$. By modeling a shared covariance structure across objectives, SMTGP captures intertask dependencies and improves predictive accuracy under data-scarce conditions.

The approximate posterior distribution can be expressed as:

$$p(f \mid X) \approx \mathcal{N}\left(K_{X,Z}K_{Z,Z}^{-1}u, K_{X,X} - K_{X,Z}K_{Z,Z}^{-1}K_{Z,X}\right), \tag{2}$$

where X is the input data, Z is the set of inducing points, u denotes the function values at the inducing points, and K denotes the covariance matrix.

D. Problem Formulation

The objective of this study is to determine optimal parameter settings for the PVD process such that multiple performance metrics fall within predefined target intervals simultaneously. Let $\mathbf{x} \in \mathbb{R}^d$ denote the input parameter vector (e.g., power, pressure, temperature), and $\mathbf{y} \in \mathbb{R}^m$ denote the output performance metrics (e.g., film thickness, uniformity). The optimization problem is formulated as:

$$\mathbf{x}^* = \arg\min_{\mathbf{x}\in\mathcal{X}} \mathbb{E}\left[\sum_{i=1}^{m} \mathbb{I}\left(y_i \notin [l_i, u_i]\right)\right], \tag{3}$$

where $y_i = f_i(\mathbf{x})$ represents the i-th performance metric, $[l_i, u_i]$ defines the desired target interval, and $\mathbb{I}(\cdot)$ is an indicator function penalizing constraint violations.

III. Methodology

A. Enhanced Bayesian Optimization for PVD Parameters

The proposed optimization framework aims to efficiently determine PVD process parameters while ensuring that deposition outcomes meet target performance metrics. However, this task presents three key challenges:

- Nonlinear dependencies among objectives: Film characteristics (e.g., thickness, uniformity) are nonlinearly correlated with process parameters (e.g., power, pressure).
- Data scarcity: High experimental costs limit the availability of training data, reducing the efficiency of conventional optimization methods.
- Target interval optimization: Traditional BO, which maximizes scalar objectives, struggles to optimize towards a target interval.

To address these challenges, we develop an Enhanced BO Framework, integrating two key components:

- SMTGP: A data-efficient surrogate model for multi-objective prediction, utilizing shared task correlations to improve accuracy in data-scarce environments.
- PRISM: A specialized acquisition function for interval optimization, guiding the search towards parameter regions most likely to meet target intervals.

These components are integrated within a BO framework, whose inherent sample efficiency enables the overall method to effectively operate under data-scarce conditions. The framework adopts practical settings: a training batch size of 4, 20

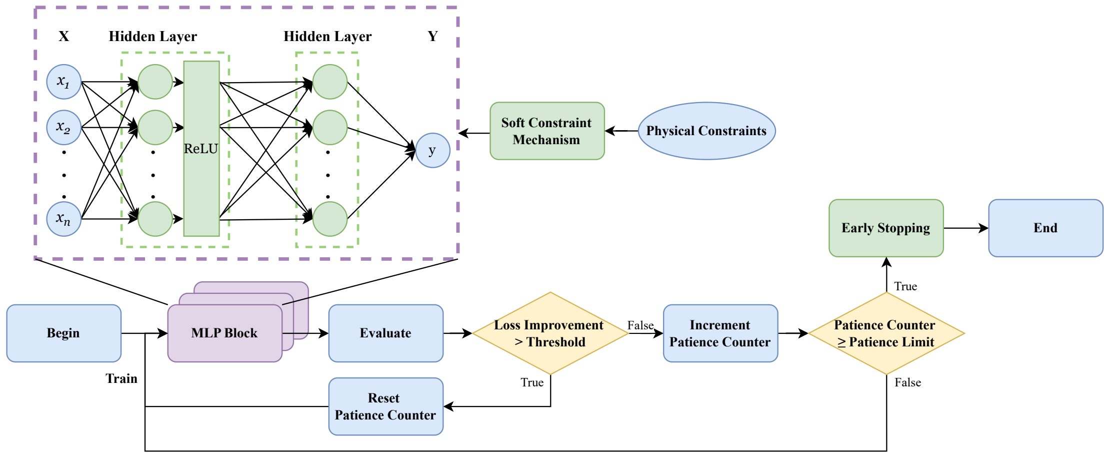

Fig. 4 MIMO Predictor with Soft Physical Constraints

inducing points, and 100 optimization epochs for the surrogate model. It follows a three-stage workflow: **Initialization**, which sets up the problem and builds the initial SMTGP model; **BO Loop**, which refines the surrogate, scores candidates using PRISM, and updates the dataset; and **Termination & Output**, which outputs optimized parameters when constraints are satisfied or stopping criteria are met. The overall process is illustrated in Fig. 3.

The following sections provide detailed descriptions of each component.

B. MIMO Predictor with Soft Physical Constraints

Due to the complexity and high cost of the actual PVD process, to optimize it efficiently, an efficient predictor is necessary to approximate the system's behavior while maintaining computational efficiency. Traditional first-principles modeling approaches are impractical due to the complex nonlinear dependencies between input parameters and performance metrics, as they require extensive computational resources. To address this, we employ a soft-constrained MIMO predictor that captures the essential input-output relationships and supports iterative optimization with limited experimental data.

MIMO Regression Model. The predictor employs a shallow Multilayer Perceptron (MLP) to predict system outcomes from input parameters. MLP is chosen for its universal function approximation capability, which allows it to effectively capture nonlinear input-output relationships while keeping computational cost low. Compared to deeper architectures, a shallow MLP reduces computational cost while preserving sufficient flexibility for accurate modeling. The MLP configuration of the model can be expressed as:

$$Y = f\left(W_2 \cdot \text{ReLU}(W_1 \cdot X + b_1) + b_2\right), \tag{4}$$

where X represents the input parameter vector, W_1 and W_2 are the weight matrices for each layer, b_1 and b_2 are the bias terms, and ReLU is the activation function that introduces nonlinearity. This model structure ensures efficient computation while capturing key dependencies within the PVD process.

Soft Constraint Mechanism. To enhance model reliability, we introduce a gradient-based penalty that reinforces the model to follow known physical trends, such as the positive correlation between power and film thickness. This mechanism reduces the impact of noisy data while preserving model adaptability to real-world deviations. The penalty term is defined as:

$$\text{Penalty} = \lambda \sum_{i=1}^{N} \max(0, \alpha_{ij} \cdot \frac{\partial y_j}{\partial x_i}), \tag{5}$$

where λ controls the strength of the constraint, and α_{ij} encodes the expected correlation between the i-th input and the j-th output, with 1 representing positive correlation and -1 indicating negative correlation. Stronger penalties are applied to well-established physical laws, ensuring the model adheres to meaningful prior knowledge without imposing rigid constraints that might misrepresent real-world variations.

Early Stopping Mechanism. To prevent overfitting, an early stopping mechanism monitors the validation loss during training. If the improvement in loss does not exceed a predefined threshold, a patience counter increments. When this counter exceeds the preset limit, training is halted, ensuring generalization while conserving computational resources. This strategy prevents unnecessary computations while also reducing the risk of overfitting to noisy data.

As shown in Figure 4, by integrating these mechanisms, the predictor effectively balances learning-based modeling with heuristic guidance. This model enables the optimization algorithm to explore process parameters efficiently while minimizing the physical experiments required.

C. Intelligent Target Interval Optimization Algorithm

Optimizing process parameters in PVD presents significant challenges. The deposition step involves multiple interdependent parameters, with slight variations potentially causing significant variations in key performance metrics. The complex, nonlinear nature of these relationships, combined with high experimental costs and data scarcity, renders direct parameter tuning impractical. An efficient optimization strategy is required to identify process configurations that satisfy

Algorithm 1 SMTGP-PRISM Multi-Objective Optimization

1) Initialize dataset $\{\mathbf{x}_i, \mathbf{y}_i\}_{i=1}^{N_{\text{init}}}$
2) Train SMTGP model
3) **for** $t = 1$ to $T_{\max}$
   - Compute PRISM acquisition function:
   $$\mathbf{x}^* = \arg\max_{\mathbf{x}} P(\mathbf{L} \le \mathbf{y} \le \mathbf{U})$$
   - Evaluate $\mathbf{x}^*$, obtain $\mathbf{y}^*$
   - Update SMTGP model
   - **if** $\mathbf{y}^*$ satisfies constraints:
     – Return $\mathbf{x}^*$ **and terminate**
4) Return failure if no valid solution is found within $T_{\max}$

performance requirements while minimizing experiments.

Traditional BO approaches are designed to optimize a single scalar objective, whereas PVD process optimization involves satisfying multiple performance metrics within predefined target intervals. To address this, we propose an optimization framework that integrates SMTGP as a surrogate model and PRISM as the acquisition function. The procedure starts by collecting an initial dataset from PVD experiments to train the SMTGP model. The trained model provides probabilistic predictions for multiple performance metrics, given a candidate process configuration. As discussed in Section II, BO iteratively selects the next input $\mathbf{x}_{t+1}$ based on the acquisition function to refine the PVD process. This SMTGP–PRISM combination enables efficient target interval optimization under data-scarce conditions. The algorithm workflow is summarized as Algorithm 1.

SMTGP. To efficiently model multiple objectives while reducing computational complexity, we employ SMTGP, a sparse multi-task GP model that introduces inducing points:

$$\mathbf{K}_{\text{full}} \approx \mathbf{K}_{XZ}\mathbf{K}_{ZZ}^{-1}\mathbf{K}_{ZX}, \tag{6}$$

where $\mathbf{K}_{XZ}$ represents the covariance between data points $\mathbf{X}$ and inducing points $\mathbf{Z}$, and $\mathbf{K}_{ZZ}$ is the covariance between inducing points. Covariance quantifies dependencies among variables, which enhances SMTGP's ability to model multiple objectives. This sparse approximation significantly reduces computational cost while preserving prediction accuracy. In our implementation, SMTGP is trained using 50 gradient descent steps with a learning rate of 0.01. To maintain efficiency in high-dimensional search spaces, we fix the number of inducing points to 20. This choice balances model scalability and approximation quality, allowing SMTGP to maintain data efficiency while capturing complex cross-objective correlations. For predictions at a new point $\mathbf{x}^*$, SMTGP provides:

$$\boldsymbol{\mu}(\mathbf{x}^*) = \mathbf{K}_{\mathbf{x}^*\mathbf{Z}}\mathbf{K}_{\mathbf{ZZ}}^{-1}\mathbf{m}_{\mathbf{Z}}, \tag{7}$$

$$\Sigma(\mathbf{x}^*) = \mathbf{K}_{\mathbf{x}^*\mathbf{x}^*} - \mathbf{K}_{\mathbf{x}^*\mathbf{Z}}\mathbf{K}_{\mathbf{ZZ}}^{-1}\mathbf{K}_{\mathbf{Z}\mathbf{x}^*}, \tag{8}$$

where $\boldsymbol{\mu}(\mathbf{x}^*)$ represents the predicted mean, and $\Sigma(\mathbf{x}^*)$ is the predictive covariance. By leveraging shared covariance structures, SMTGP effectively captures multi-objective correlations, enhancing prediction accuracy under limited data conditions.

PRISM. Unlike conventional BO acquisition functions that prioritize point-wise improvement, PRISM uses the probability that all objectives fall within predefined intervals as the optimization criterion, guiding the search toward input parameters that are more likely to satisfy practical multi-objective specifications. It computes the probability of outputs falling within predefined target intervals:

$$P(\mathbf{L} \le \mathbf{y} \le \mathbf{U}) = \int_{\mathbf{L}}^{\mathbf{U}} \mathcal{N}(\mathbf{y} \mid \boldsymbol{\mu}, \Sigma)\, d\mathbf{y}, \tag{9}$$

where $\boldsymbol{\mu}$ and Σ are predicted by SMTGP, and $\mathbf{L}$ and $\mathbf{U}$ denote the interval bounds. In practice, PRISM evaluates 100 randomly generated candidates within the input domain and applies 5 rounds of local refinement using the L-BFGS-B algorithm to maximize the interval probability. This two-phase search strategy improves the likelihood of identifying promising regions early while ensuring precise convergence. PRISM serves as the acquisition function:

$$\text{PRISM}(\mathbf{x}) = P(\mathbf{L} \le \mathbf{y} \le \mathbf{U}), \tag{10}$$

by selecting the candidate point that maximizes this probability, ensuring that new samples are both informative, and aligned with target interval constraints, thereby reducing experimental costs and enabling scalable optimization for complex semiconductor processes such as PVD.

IV. Evaluation

A. Experimental Settings

The optimization task aims to identify process parameters (e.g., temperature, pressure, power) such that multiple performance metrics (e.g., film thickness, uniformity) fall within predefined target intervals $[l_i, u_i]$, $\forall i = 1, \ldots, m$. Given the high cost of real-world experiments, we employ a predictive model to approximate performance metrics and efficiently explore the search space.

All experiments are conducted using a high-performance computing system with *Intel Xeon processors* and *NVIDIA RTX 3090 GPUs*. The implementation is developed in `Python`, utilizing `PyTorch` for surrogate modeling, `GPyTorch` for Gaussian process regression, and standard numerical computation libraries.

Problem Configurations. To evaluate the algorithm's performance, we construct multiple benchmark cases with varying complexity, including 4-input 4-output, 6-input 6-output, and 10-input 10-output configurations. Each setup is tested under both wide-range and narrow-range target intervals to simulate different optimization difficulties. A fixed number of initial samples are provided, and the optimization runs until a valid solution is found or a predefined iteration limit is reached.

Baselines. The proposed algorithm is compared against two classical methods as benchmarks for optimization efficiency:

- Random Search (RS): A baseline method that relies entirely on random sampling.
- BO: A classical approach utilizing GPR to model the objective functions and standard acquisition functions (e.g., Expected Improvement, EI, a commonly used approach for global optimization) for optimization guidance.

TABLE I Main Experimental Results

Scenario	RS		BO		Ours	
	Aver.	SR	Aver.	SR	Aver.	SR
4I4O-W	217	21%	68	72%	**25**	**92%**
4I4O-N	476	14%	103	71%	**37**	**89%**
6I6O-W	N/A	N/A	183	52%	**105**	**81%**
6I6O-N	N/A	N/A	248	36%	**138**	**77%**
10I10O-W	N/A	N/A	N/A	N/A	**264**	**65%**
10I10O-N	N/A	N/A	N/A	N/A	**308**	**64%**

Metrics. To assess performance, we adopt two key metrics:

- Average Number of Experiments (Aver.): Measures the mean number of trials required to find a solution satisfying all target intervals.
- Success Rate (SR): Represents the proportion of optimization experiments that successfully find a valid solution within a predefined iteration limit.

These metrics collectively quantify the trade-off between optimization efficiency and solution feasibility.

Datasets. The dataset originates from a benchmark task provided by NAURA during the 2024 ICT Industry-Academia Innovation Competition. While the original dataset is 4-input 4-output, higher-dimensional variants are extended using domain knowledge to test scalability. Although these data have undergone special processing, they retain key process characteristics for validation.

While SMTGP substantially reduces the theoretical complexity via sparse approximation, the multi-objective modeling and interval-based acquisition still incur non-negligible overhead, suggesting room for future acceleration.

B. Performance Comparison and Ablation Study

The experimental results in Table I highlight the efficiency and reliability of the proposed algorithm across various problem dimensions. The scenarios 4I4O, 6I6O, and 10I10O correspond to optimization tasks with 4, 6, and 10 inputs and outputs, respectively, evaluated under wide-range (W) and narrow-range (N) constraints. Performance is measured using two metrics: Aver. and SR. If the SR is too low, it indicates poor performance of the optimization method in that scenario. This often results in high randomness and unreliable outcomes. In such cases, we mark the results as N/A.

The proposed algorithm outperforms baseline methods in all scenarios. In low-dimensional problems (4I4O), it significantly reduces the number of evaluations required compared to BO, particularly in narrow-range constraints. For medium-dimensional problems (6I6O), the improvement is more pronounced, with SR increasing by over 40 percentage points compared to BO. In high-dimensional cases (10I10O), only our method successfully finds feasible solutions, achieving an SR exceeding 60%, whereas other methods rarely succeed. RS fails to produce valid solutions beyond low dimensions, highlighting its inefficiency in complex settings.

The key advantages of our approach are: (1) PRISM enables targeted exploration, thus avoiding unnecessary sampling. (2) SMTGP captures multi-objective dependencies, improving model accuracy. (3) Their combination ensures robust performance, even in high-dimensional spaces.

TABLE II Ablation Study: Impact of PRISM and SMTGP

Scenario	Full (Ours)		No PRISM		No SMTGP	
	Aver.	SR	Aver.	SR	Aver.	SR
4I4O-W	**25**	**92%**	70	37%	52	77%
4I4O-N	**37**	**89%**	107	36%	77	73%
6I6O-W	**105**	**81%**	285	35%	219	67%
6I6O-N	**138**	**77%**	391	31%	305	63%

To further analyze the impact of PRISM and SMTGP, we conduct an ablation study on two optimization settings: 4I4O and 6I6O. We compare the full model (SMTGP + PRISM) with two ablated versions, as summarized in Table II: (1) No PRISM: Replacing PRISM with EI while keeping SMTGP. (2) No SMTGP: Replacing SMTGP with independent GPR while keeping PRISM.

Effect of PRISM. Removing PRISM and using EI as the acquisition function leads to a substantial increase in evaluations and a significant drop in SR across both 4I4O and 6I6O settings. This effect is more pronounced in the narrow constraint setting, where SR drops below 40%. Since EI focuses on point-wise improvement rather than interval coverage, it struggles to navigate the feasible region efficiently.

Effect of SMTGP. Without SMTGP, optimization requires a significantly higher number of evaluations, and SR drops noticeably in both scenarios. Independent GPR models fail to leverage correlations between objectives, resulting in a less efficient search. This is particularly evident in the wide-range constraint setting, where the lack of a structured multi-task model reduces sample efficiency.

The ablation study shows that both PRISM and SMTGP are crucial for efficient multi-objective interval optimization. PRISM plays a dominant role by guiding the search toward feasible regions, while SMTGP improves sample efficiency by modeling inter-objective correlations. Removing PRISM causes a greater performance degradation, especially under narrow constraints.

Due to the proprietary nature of industrial PVD data, real-world validation is currently unavailable; future work will explore collaborations with industry partners to further evaluate the framework's practical applicability.

V. Conclusion

This study proposes an intelligent optimization method for PVD parameter tuning, aiming to address challenges arising from nonlinear complexity, multi-objective constraints, and data scarcity. By integrating SMTGP and PRISM within a BO framework, the proposed method effectively captures nonlinear relations, improves efficiency, and reduces experimental costs. Experiments show it outperforms RS and classical BO in both efficiency and target satisfaction, especially in high-dimensional scenarios. The method offers a promising solution for parameter optimization in semiconductor manufacturing.

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