Cross-Wavelength Correlation Dynamic Multi-Objective Optimization for Optical Sensor Design

1st Ru Lei*
School of Automation
Northwestern Polytechnical University
Xi'an, China
leir@mail.nwpu.edu.cn

2nd Lin Li*
School of Automation
Northwestern Polytechnical University
Xi'an, China
linli@nwpu.edu.cn

3rd Kun Zhang
School of Automation
Northwestern Polytechnical University
Xi'an, China
zhangkun123@mail.nwpu.edu.cn

4th Yiqi Feng
School of Automation
Northwestern Polytechnical University
Xi'an, China
yiqifeng@mail.nwpu.edu.cn

5th Jiao Shi
School of Electronics and Information
Northwestern Polytechnical University
Xi'an, China
jiaoshi@nwpu.edu.cn

6th Chen Xia
School of Automation
Northwestern Polytechnical University
Xi'an, China
cxia@nwpu.edu.cn

***Abstract*—This paper proposes a cross-wavelength correlation based dynamic multi-objective optimization (DMO) framework for multilayer optical device design. Such structures require balancing optical performance and structural compactness. Optimal layer configurations at different wavelengths are not independent but exhibit intrinsic cross-wavelength correlations. To exploit this property, the proposed algorithm extracts information from previously optimized wavelengths to predict promising regions for the next wavelength and provides correlation-aware initialization, thereby reducing redundant exploration and improving convergence efficiency. The framework produces a diverse set of Pareto set(PS) that trade off near-perfect absorption and compact multilayer sensor structures. We further develop a prediction-driven DMO tailored to this design task and validate it through numerical simulations on representative multilayer design cases. The results show that the proposed approach can reliably obtain robust and structurally compact designs under multi-wavelength requirements, while maintaining strong absorption performance and efficient convergence. This study demonstrates an effective real-world deployment of DMO and facilitates efficient design of multilayer optical sensor devices and related sensing technologies.**

***Index Terms*—Dynamic multi-objective optimization, Cross-wavelength correlation, Multilayer structure optimization.**

I. Introduction

In thin-film photonics have demonstrated that multilayer optical sensor structures can be engineered to exhibit highly selective absorption characteristics at prescribed wavelengths [1]. Achieving such wavelength-specific responses requires careful adjustment of layer thicknesses and material properties, and the resulting performance is governed by complex interactions among multiple physical parameters. As a result, multilayer structure design has become a representative and challenging engineering problem, especially when multiple target wavelengths must be considered simultaneously.

The design of multilayer thin-film (MTF) structures [2] typically involves alternating layers with different refractive indices, whose thicknesses collectively determine the resulting interference patterns and spectral characteristics. By properly selecting these parameters, near-perfect absorption can be achieved at target wavelengths through constructive and destructive interference effects [3]. However, increasing the number of layers or total thickness generally improves absorption performance at the cost of reduced compactness, while simpler structures favor compactness but sacrifice spectral selectivity. This inherent trade-off leads to the multi-objective optimization problems (MOPs) that becomes increasingly complex when multiple wavelengths are considered simultaneously.

This progress naturally motivates a computational formulation of multilayer design as a numerical optimization problem [4, 5]. In particular, competing requirements such as absorption performance and structural compactness must be jointly considered, which leads to a MOP perspective. Moreover, as design conditions vary across wavelengths, traditional manual tuning or static optimization methods gradually exhibit low efficiency. Multilayer designs targeting multiple wavelengths cannot be treated as independent optimization problems. The optimal configurations corresponding to different wavelengths are closely related, yet not identical, and exhibit structured variations across the wavelength dimension. As a result, repeatedly solving independent static optimization problems leads to redundant computations and poor scalability. These characteristics highlight the need for dynamic multi-objective optimization algorithms (DMOAs) [6–8] that can exploit relationships among a sequence of related design tasks and efficiently track high-quality solutions as design conditions vary.

To address these challenges, we propose a prediction-based

DMOAs tailored to multilayer structure of sensor design problems. Instead of optimizing each wavelength independently, the proposed method treats designs at different wavelengths as a sequence of related optimization tasks and exploits cross-wavelength information to guide the search process. Historical optimization results are used to predict promising regions in the design space for subsequent wavelengths, enabling efficient warm-starting and accelerated convergence. Compared with conventional static optimization approaches [9, 10], the proposed framework significantly improves optimization efficiency while maintaining solution quality across multiple wavelengths.

Our key contributions are as follows.

- This work presents a novel application of dynamic multi-objective optimization to multilayer optical structure design under varying wavelength requirements. By formulating the design process as a sequence of related optimization tasks, the proposed framework extends the application scope of dynamic multi-objective optimization and demonstrates its practical value in complex engineering design problems.
- The proposed approach provides a systematic solution for wavelength-sensitive multilayer optical sensor design, where optical performance and structural compactness must be jointly optimized. By explicitly addressing multi-wavelength requirements, the framework enables robust and compact sensor designs.
- A prediction-based dynamic multi-objective optimization method is developed to exploit cross-wavelength information and guide the search process. By using historical optimization results to initialize and steer subsequent searches, the proposed method improves convergence efficiency and stability in dynamic optimization scenarios.

II. Related Works

A wide range of static optimization algorithms have been applied to the design of MTFs. Jiang et al. [11] integrated unsupervised learning, reinforcement learning, and genetic algorithms to realize the fully autonomous design of optical thin films. Wang et al. [12] formulated the multilayer optical coating design as a sequence generation problem and employed deep reinforcement learning with proximal policy optimization, surpassing both human experts and state-of-the-art algorithms. Lin et al. [13] precisely tuned the signal of a multilayer dielectric–based surface plasmon resonance sensor by optimizing both the individual layer thickness and the total number of layers. Despite these advances, static optimization techniques are fundamentally limited to fixed operating conditions. Once the wavelength of incident light varies, these methods must re-initialize the entire optimization process, discarding prior results. Such repeated re-optimization not only incurs high computational costs but also overlooks correlations across neighboring environmental states. Consequently, static methods are inefficient for scenarios that require rapid adaptation to dynamically changing conditions. This limitation motivates the adoption of DMOAs, which use historical solutions to predict, adjust, and sustain high performance under continuous spectral variations.

Among existing strategies for DMOAs [6, 14–17], prediction-driven approaches have emerged as the mainstream direction. Guo et al. [14] proposed a knowledge-guided dynamic multi-objective optimization strategy that effectively improves optimization efficiency in dynamic environments. Xu et al. [16] introduced a co-evolutionary multi-population algorithm to adapt to changes in dynamic multi-objective environments. Lei et al. [6] incorporated an adaptive dual-domain perspective to simultaneously capture historical features in both the objective and decision spaces. Wang et al. [17] proposed an MOEA/D [9] framework with spatial-temporal topological tensor prediction, which explicitly models the spatial and temporal dependencies among subproblems to predict the evolution of optimal solutions in dynamic environments. Ye et al. [18] introduced a learning-based directional improvement prediction method, where a predictive model is trained to estimate promising search directions rather than directly predicting solution positions. Hu et al. proposed RNN [19], is guided by a recurrent neural network. It can learn the variation patterns of objective functions in dynamic environments and predict their future behavior to guide the optimization process. Li et al. proposed HRS-MOEA/D [20] is equipped with a hierarchical response system. It dynamically adjusts its behavior and strategies based on the degree of objective function changes and the adaptability of the population. Xu et al. proposed IMD-MOEA/D [21], which is a clustering prediction strategy based on induced mutation. It partitions the population into multiple clusters through clustering analysis and then predicts the future positions and distributions of these clusters under dynamic environments.

This strategy enables the algorithm to adaptively guide population evolution toward favorable regions of the PF. This core idea is to exploit historical solutions to estimate the evolution of the environment, thereby enabling the rapid generation of high-quality candidate solutions in new scenarios. Compared with passive re-optimization, prediction methods not only significantly reduce convergence time but also establish correlations across different environmental states. For example, in the design of optical multilayer films under adjacent wavelengths, predictive mechanisms can use the continuity of spectral variations to enhance both efficiency and robustness in multichannel scenarios. This motivates our wavelength-sensitive prediction framework for optical sensor design.

III. Proposed algorithm

A. Multilayer Optical Sensor Structure

The proposed multichannel optical sensor is based on a wavelength-sensitive MTF, as illustrated in Fig. 1. Each sensing unit consists of alternating TiO_2 (high-refractive index) and SiO_2 (low-refractive index) layers stacked on a substrate, σ_g denotes the conductivity of graphene, which sheet is placed on top, exposed to air. The graphene layer further enhances absorption and provides a tunable optical response, while the multilayer stack achieves selective absorption or reflection at

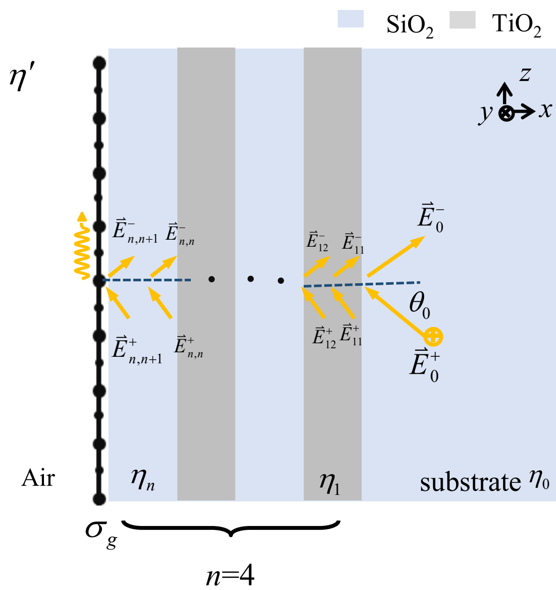

Fig. 1: Illustration of graphene-coated MTF.

target wavelengths through optical interference control. The electromagnetic boundary conditions at the high/low refractive index interfaces inherently create a trade-off between achieving near-perfect absorption and maintaining a compact multilayer configuration. The key design variables include the number of periods n, the thicknesses of layer, and the angle of incidence θ_0. By carefully adjusting these parameters, the structure can maximize absorption across multiple spectral channels simultaneously, enabling efficient modulation of multichannel optical signals for optical sensing applications.

The optical properties of the graphene-coated MTF: reflectance R, transmittance T, and absorptance A, are show in Eq. 1.

$$\begin{cases} R = \left(\dfrac{\eta_0 B - C}{\eta_0 B + C}\right)\left(\dfrac{\eta_0 B - C}{\eta_0 B + C}\right)^* \\ T = \dfrac{4\eta_0\eta_{n+1}}{(\eta_0 B + C)\,(\eta_0 B + C)^*} \\ A = 1 - R - T \end{cases} \tag{1}$$

$$\begin{bmatrix} B \\ C \end{bmatrix} = \left(\prod_{l=1}^{n-1} \begin{bmatrix} \cos\delta_l & -i\frac{\sin\delta_l}{\eta_l} \\ -i\eta_l \sin\delta_l & \cos\delta_l \end{bmatrix}\right) \cdot D_g \cdot \begin{bmatrix} 1 \\ \eta_{n+1} \end{bmatrix} \tag{2}$$

where $\eta_l = \sqrt{\mu_0/\varepsilon_0}, n_l \cos\theta_l$ is the TE-mode [22] admittance of the l-th layer, $\delta_l = 2\pi n_l d_l \cos\theta_l/\lambda$ is the phase shift with thickness d_l and wavelength λ (in the visible range, $\lambda \in [380nm, 760nm]$). D_g denotes the transfer matrix of graphene. This formulation describes wave propagation and the resulting reflection and transmission across multilayer interfaces.

$$\begin{cases} f_1(\mathbf{x}, \lambda) = \dfrac{1}{A(\mathbf{x}, \lambda)} \\ f_2(\mathbf{x}, \lambda) = \displaystyle\sum_{l=1}^{n} d_l \end{cases} \tag{3}$$

where the problem is formulated as a multi-objective minimization task. Since the absorptance A is a performance measure to be maximized, the first objective is defined as its reciprocal, i.e., $f_1(\mathbf{x}, \lambda) = 1/A(\mathbf{x}, \lambda)$, so that minimizing f_1 is equivalent to maximizing A. The second objective $f_2(\mathbf{x}, \lambda) = \sum_{l=1}^{n} d_l$ measures structural compactness by the total thickness, and minimizing f_2 yields a more compact multilayer design. Although $f_2(\mathbf{x}, \lambda)$ does not explicitly depend on λ, it varies across wavelengths through the wavelength-dependent optimal solution $\mathbf{x}(\lambda)$.

$$\lambda = t = \frac{1}{n_t}\left\lfloor \frac{\tau}{\tau_t} \right\rfloor, \tag{4}$$

where n_t is the severity of environmental change, τ_t is the number of generations with unchanged t, and τ is the total generation per environment. Optimization aims to maximize absorptance A for efficient light coupling, and minimize structural complexity $f_2(\mathbf{x}, \lambda)$, which is defined by the number of graphene layers N_g and the number of periods with high/low refractive index N_T, to achieve compact and fabrication-friendly designs.

The overall framework of the proposed dynamic multi-objective optimization approach is illustrated in Algorithm 1. The algorithm iteratively tracks the optimal solutions as the wavelength varies, and switches between a static optimization strategy and a dual-space prediction-based MOEA according to the detected environmental changes.

Algorithm 1 Overall Framework for Dynamic Multi-Objective MTF Design

Require: Wavelength sequence $\{\lambda_t\}_{t=0}^{T}$; initial population size N
Ensure: Final optimized populations $\{P_t\}$ and Pareto fronts $\{PF_t\}$

```
Initialize t ← 0
Randomly initialize population P_0 with size N
Evaluate objective functions and obtain PF_0
while t < T do
    Set t ← t + 1
    Obtain current wavelength λ_t
    Detect environmental change: Δ_t ← (λ_t ≠ λ_{t−1})
    if Δ_t then
        Perform Algorithm 2
    else
        Perform static MOEA at λ_t initialized by P_{t−1} to obtain P_t
    end if
    Evaluate objective functions of P_t and update PF_t
end while
return {P_t}, {PF_t}
```

B. Dynamic Multi-objective Optimization

Fig. 2 illustrates the reflectance and absorptance behavior of TE-mode light in varying incident wavelengths and angles.

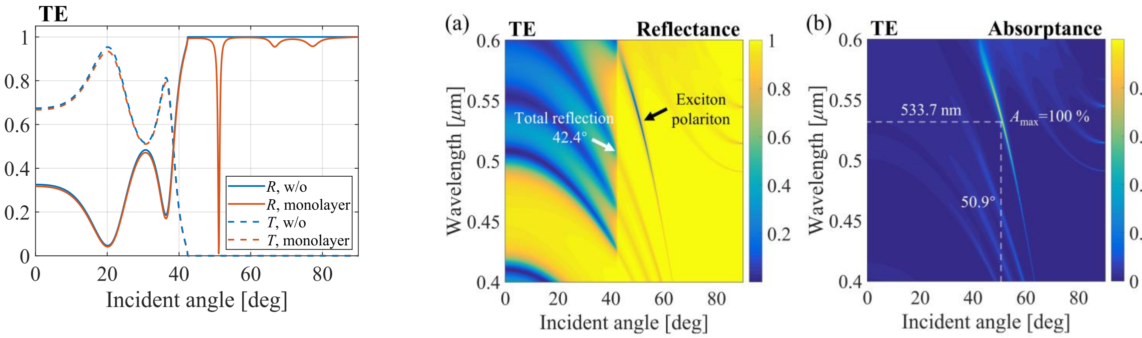

Fig. 2: The R, T, and A behavior of TE-mode light in varying incident wavelengths and angles.

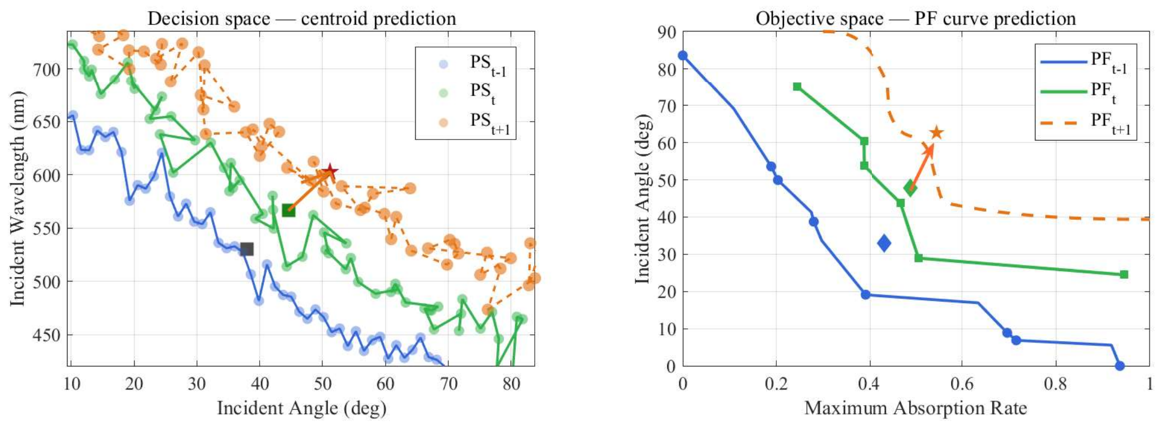

Fig. 3: The proposed method.

Algorithm 2 Dual-Space Prediction MOEA for Multilayer Thin-Film (MTF) Design

Require: Current wavelength λ_t; historical population P_{t-1}; historical fronts PF_{t-1} and PF_{t-2}
Ensure: Optimized population P_t
Generate predicted solutions $\widehat{PS}_t$ from historical solutions in P_{t-1}
Predict Pareto front $\widehat{PF}_t$ using PF_{t-1} and PF_{t-2}
Map $\widehat{PF}_t$ to decision space and obtain $\widehat{PM}_t$
Construct initial population $P_t \leftarrow \widehat{PS}_t \cup \widehat{PM}_t$
Evaluate objective functions of P_t
while termination condition not met **do**
    Apply selection, crossover, and mutation operators
    Update population P_t
    Evaluate objective functions and update the current front PF_t
end while
return P_t

In Fig. 2 (a) shows the reflectance, where the total reflection occurs at an incident angle of 42.4°. Fig. 2 (b) depicts the absorptance variation, with a maximum absorptance observed at a wavelength of 533.7 nm and an incident angle of 50.9°. These results highlight the high sensitivity of MTF excitation to both wavelength and angle of incidence. Such strong wavelength and angle dependence implies that the optimal multilayer configuration varies continuously with environmental conditions. Therefore, designing high-performance MTF across multiple wavelengths naturally leads to a dynamic multi-objective optimization problem, where the algorithm must adaptively track the Pareto-optimal solutions as the incident wavelength changes.

To efficiently address the dynamic multi-objective nature of the multilayer sensor design, we adopt a dual-space prediction strategy as the Fig. 3. In this framework, both the decision space and the objective space are exploited to guide the search. In the decision space, the centroid of the Pareto solutions(PS) [23] from previous wavelength states is used to predict candidate layer configurations for new wavelengths. This approach captures the continuity in optimal layer thicknesses and the number of periods, enabling rapid convergence without reinitializing the entire population. In the objective space, the shape and distribution of the Pareto front (PF) [23] are tracked and predicted across wavelengths. By estimating the PF evolution, the algorithm can maintain diversity among candidate solutions while guiding the search toward compact and high absorptance designs. By integrating decision-space and objective-space predictions, the proposed algorithm ef-

TABLE I: Performance Metrics Values Obtained by the Compared Algorithms with Four Dynamic Configurations

Performance Metrics	n_t,τ_t	HRS-MOEA/D [20]	IMD-MOEA/D [21]	RNN-MOEA/D [19]	Our method
MA	5,5	42.0% (4.61e-2)+	74.6% (1.58e-2)+	41.3% (1.61e-2)+	**79.2% (2.75e-2)-**
	5,10	45.6% (2.35e-2)+	82.8% (1.32e-2)=	53.0% (6.65e-2)+	**85.7% (3.14e-3)-**
	10,10	47.1% (2.81e-2)+	84.0% (1.45e-2)+	55.2% (5.92e-2)+	**87.0% (3.87e-3)-**
MIGD	5,5	**3.4821e-1 (8.92e-3)-**	4.1586e-1 (1.28e-2)+	4.5012e-1 (2.33e-2)+	4.0497e-1 (9.12e-3)+
	5,10	4.2614e-1 (3.01e-3)=	4.3051e-1 (7.24e-3)=	4.5382e-1 (1.05e-2)+	**4.2493e-1 (5.64e-3)-**
	10,10	4.1837e-1 (4.26e-3)=	4.2215e-1 (6.91e-3)+	4.6124e-1 (1.18e-2)+	**4.1769e-1 (5.21e-3)-**
MHV	5,5	7.921e-1 (2.15e-2)+	8.2431e-1 (8.76e-2)=	6.1328e-1 (3.05e-2)+	**8.2746e-1 (1.02e-2)-**
	5,10	8.267e-1 (1.21e-2)+	8.3972e-1 (6.41e-2)=	6.4881e-1 (4.85e-2)+	**8.5213e-1 (4.87e-3)-**
	10,10	8.3142e-1 (1.67e-2)+	8.4568e-1 (5.98e-2)+	6.7025e-1 (4.11e-2)+	**8.6137e-1 (5.36e-3)-**
+/-/=		7/1/1	5/0/4	9/0/0	——

ficiently generates multichannel thin-film configurations that maximize absorption across multiple wavelengths while respecting fabrication constraints.

IV. EXPERIMENTAL ANALYSIS

The following experiment demonstrates the effectiveness of the proposed algorithm. The group benchmarks our method against three state-of-the-art algorithms, namely HRS-MOEA/D [20], IMD-MOEA/D [21], and RNN-DMOEA [19].

The comparative performance of the proposed method and baseline algorithms is evaluated using three metrics: mean absorptance (MA), which measures the average absorptance of MTF designs under varying wavelength conditions; mean inverted generational distance (MIGD) [24], which quantifies the convergence quality of the obtained PF, lower values are better; and mean hypervolume difference (MHV) [25], where larger values indicate stronger convergence and population diversity. The experimental results, averaged over 20 independent runs, are summarized in Table I. To assess statistical significance, the Wilcoxon rank sum test [26] is employed with a 5% confidence level. The symbols "+", "–", and "=" denote whether the proposed algorithm performs significantly better, worse, or similarly compared to the corresponding method, respectively.

As shown in Table I, the proposed algorithm achieves superior overall performance. In terms of MA, which reflects absorptance capability, our method yields the highest values in all three cases, consistently exceeding 79%. It significantly outperforms HRS-MOEA/D and RNN-DMOEA, while being comparable to or better than IMD-MOEA/D. For MIGD, the proposed approach achieves the lowest scores in two of three scenarios, demonstrating a faster and more accurate convergence towards the PF. Regarding MHV, our method consistently delivers the best results, indicating greater diversity and convergence quality of the population. Collectively, these consistent improvements across all three indicators highlight the effectiveness and robustness of the proposed approach. Moreover, the Wilcoxon statistical test confirms that our method achieves the highest number of significant wins among all compared algorithms, further validating its robustness and superiority.

TABLE II: Decision Values Obtained by our method

Absorption	Wavelength	d_{SiO_2}	d_{TiO_2}	Inc$_{angle}$	N_g	N_T
96.8%	385 nm	472 nm	446 nm	83.9°	5	3
99.6%	530 nm	561 nm	85 nm	61.2°	4	3
98.7%	635 nm	698 nm	215 nm	79.8°	4	2

Table II summarizes the representative values of decision variable obtained by the proposed at different target wavelengths. It can be observed that the number of graphene layers and thickness of MTF remain relatively small, which highlights the structural compactness and ease of fabrication. This balances high absorptance and low structural complexity.

V. CONCLUSION

In this work, we proposed a prediction-driven dynamic multi-objective optimization framework and demonstrated its effectiveness through a novel application to wavelength-sensitive multilayer structure design. By exploiting correlations among optimal designs across varying wavelengths, the proposed approach enables efficient tracking of Pareto-optimal solutions while achieving a favorable trade-off between high absorptance and structural simplicity. The results confirm that dynamic multi-objective optimization can serve as a practical and powerful tool for solving complex engineering design problems. Future work will focus on bridging the proposed optimization framework with experimental optical platforms. In particular, we plan to incorporate practical fabrication considerations and collaborate with optical laboratories to validate the optimized designs through physical experiments. From a methodological perspective, further research will explore more efficient prediction and adaptation strategies to enhance scalability and convergence speed in dynamic optimization scenarios.

REFERENCES

[1] T. Ma, M. Ma, and L. J. Guo, "Optical multilayer thin film structure inverse design: From optimization to deep learning," *iScience*, vol. 28, no. 4, p. 112222, 2025.

[2] K. C. and N. P. et al., "Mass-production-enabled computational spectrometer based on multilayer thin films," *Scientific Reports*, vol. 12, p. 4053, 2022.

[3] A. S. Rana and M. Z. et al., "Engineering the absorption spectra of thin film multilayer absorbers for enhanced color purity in cmy color filters," *Opt. Mater. Express*, vol. 10, no. 2, pp. 268–281, Feb 2020.

[4] M. A. Butt and X. M. et al., "Photonics sensors: A perspective on current advancements, emerging challenges, and potential solutions," *Physics Letters A*, vol. 516, p. 129633, 2024.

[5] T. M. S. Ashrafi and M. Goutam, "Surface plasmon resonance sensors: A critical review of recent advances, market analysis, and future directions," *Plasmonics*, 2025.

[6] R. Lei and L. L. et al., "An adaptive dual-domain prediction strategy based on second-order derivatives for dynamic multi-objective optimization," *IEEE Transactions on Evolutionary Computation*, pp. 1–1, 2025.

[7] R. Lei, K. Zhang, L. Li, Y. Guo, Y. Feng, L. Sun, F. Tong, R. Stolkin, and M. E. Asif, "Online-updating neural network with decentralized prediction for dynamic multi-objective optimization," *Expert Systems with Applications*, vol. 315, p. 131651, 2026.

[8] J. Zou, Z. Hou, S. Jiang, S. Yang, G. Ruan, Y. Xia, and Y. Liu, "Knowledge transfer with mixture model in dynamic multiobjective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 5, pp. 1517–1530, 2025.

[9] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 6, pp. 712–731, 2007.

[10] L. Li and R. L. et al., "A dual-channel deep learning method for demosaicing based on an optimized color-polarization array," *IEEE Sensors Journal*, pp. 1–1, 2025.

[11] A. Jiang, L. Chen, and Y. Osamu, "A reinforcement learning method for optical thin-film design," *arXiv preprint arXiv:2102.09398*, 2021.

[12] H. Wang and Z. Z. et al., "Automated multi-layer optical design via deep reinforcement learning," *Third Workshop on Machine Learning and the Physical Sciences*, 2020.

[13] C. W. Lin and K. P. C. et al., "Design and fabrication of an alternating dielectric multi-layer device for surface plasmon resonance sensor," *Sensors and Actuators B: Chemical*, vol. 113, no. 1, pp. 169–176, 2006.

[14] Y. Guo and G. C. et al., "A knowledge guided transfer strategy for evolutionary dynamic multiobjective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 27, no. 6, pp. 1750–1764, 2023.

[15] Y. Liu, L. Tang, J. Ding, Q. Chen, K. Liu, and J. Liu, "A dual mutation-based evolutionary algorithm for dynamic multiobjective optimization with undetectable changes," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 4, pp. 1199–1214, 2025.

[16] X. X. Xu and J. Y. L. et al., "A co-evolutionary multi-population evolutionary algorithm for dynamic multiobjective optimization," *Swarm and Evolutionary Computation*, vol. 89, p. 101648, 2024.

[17] X. Wang, Y. Zhao, L. Tang, and X. Yao, "Moea/d with spatial–temporal topological tensor prediction for evolutionary dynamic multiobjective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 3, pp. 764–778, 2025.

[18] Y. Ye, S. Liu, J. Zhou, Q. Lin, M. Jiang, and K. Chen Tan, "Learning-based directional improvement prediction for dynamic multiobjective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 4, pp. 948–962, 2025.

[19] H. Yaru and O. J. et al., "Dynamic multi-objective optimization algorithm guided by recurrent neural network," *IEEE Transactions on Evolutionary Computation*, pp. 1–1, 2024.

[20] H. Li and Z. W. et al., "A novel dynamic multiobjective optimization algorithm with hierarchical response system," *IEEE Transactions on Computational Social Systems*, vol. 11, no. 2, pp. 2494–2512, 2024.

[21] K. Xu and Y. X. et al., "A cluster prediction strategy with the induced mutation for dynamic multi-objective optimization," *Information Sciences*, vol. 661, p. 120193, 2024.

[22] T. Aghaee and A. A. Orouji, "Reconfigurable multi-band, graphene-based thz absorber: circuit model approach," *Results in Physics*, vol. 16, p. 102855, 2020.

[23] K. Deb, "Multi-objective optimisation using evolutionary algorithms: an introduction," *Multi-objective evolutionary optimisation for product design and manufacturing*, pp. 3–34, 2011.

[24] Z. Eckart and T. L. et al., "Performance assessment of multiobjective optimizers: An analysis and review," *IEEE Transactions on evolutionary computation*, vol. 7, no. 2, pp. 117–132, 2003.

[25] W. Lyndon and H. P. et al., "A faster algorithm for calculating hypervolume," *IEEE transactions on evolutionary computation*, vol. 10, no. 1, pp. 29–38, 2006.

[26] F. Wilcoxon, "Individual comparisons by ranking methods," *Breakthroughs in statistics: Methodology and distribution*, pp. 196–202, 1992.