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Abstract

With the development of new highly coherent accelerator light sources such as fourth-generation synchrotron radiation sources and Steady-State Microbunching (SSMB), tasks including beamline design, online optimization, and virtual diagnostics impose increasing demands on fast and high-accuracy optical-field prediction. However, high-accuracy simulations based on wave optics are usually computationally expensive and are difficult to use for real-time evaluation. Meanwhile, radiation spot patterns from highly coherent accelerator light sources exhibit pronounced high dynamic range and complex diffraction-fringe structures. Surrogate models constructed in the conventional linear intensity space are easily dominated by the central high-intensity region, resulting in insufficient prediction of weak-intensity diffraction structures at the periphery. To address this issue, this paper proposes an end-to-end surrogate modeling framework for radiation spots from highly coherent accelerator light sources based on a logarithmic manifold representation. The method maps the nonnegative light-intensity field onto a logarithmic manifold, constructs surrogate models in this space, and recovers the original linear space through an inverse mapping. Theoretical analysis shows that the Euclidean error in logarithmic space corresponds, under a first-order approximation, to the relative error in the original intensity space; therefore, this representation can better match relative-error evaluation metrics for high-dynamic-range intensity fields. As a validation of the method, this paper adopts an SRW undulator radiation spot case under fourth-generation synchrotron radiation source parameters, and systematically compares the predictive performance of four types of surrogate models, namely POD-Linear, POD-Quadratic, POD-ANN, and End-to-End Encoder-Decoder, in both linear space and the logarithmic manifold. Numerical results show that, after introducing the logarithmic manifold mapping, the mean relative errors of all four models are significantly reduced. Moreover, the trained surrogate models can achieve millisecond-level single-sample prediction, substantially reducing the computational cost compared with high-accuracy SRW wave-optics simulations. These results demonstrate that the logarithmic manifold representation is a general representation-space improvement method suitable for surrogate modeling of high-dynamic-range radiation spots, and can provide a technical route for fast optical-field prediction, online optimization, and virtual diagnostics for future highly coherent accelerator light sources such as SSMB.

Full Text

Study of a Surrogate Modeling Method for Radiation Patterns from Coherent Accelerator Light Sources Based on Log-Manifold Representation

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Abstract With the development of new highly coherent accelerator light sources such as fourth-generation synchrotron radiation sources and steady-state microbunching (SSMB), tasks such as beamline design, online optimization, and virtual diagnostics have placed higher demands on rapid and high-accuracy prediction of optical fields. However, high-fidelity simulations based on wave optics are usually computationally expensive and difficult to meet the needs of real-time evaluation. Meanwhile, radiation patterns from highly coherent accelerator light sources have a remarkably high dynamic range and complex diffraction-fringe structures. Surrogate models constructed in the traditional linear intensity space are easily dominated by the central high-intensity region, resulting in insufficient prediction of weak-intensity diffraction structures at the edges. To address this problem, this paper proposes an end-to-end surrogate modeling framework for radiation patterns from highly coherent accelerator light sources based on log-manifold representation. This method maps nonnegative optical intensity fields onto a log manifold, constructs surrogate models in this space, and restores the results to the original linear space through inverse mapping. Theoretical analysis shows that, under a first-order approximation, the Euclidean error in log space corresponds to the relative error in the original intensity space; therefore, this representation can better match relative-error evaluation metrics for optical fields with high dynamic range. As a methodological validation, this paper adopts an SRW wave-optics radiation-pattern example under parameters of a fourth-generation synchrotron radiation source, and systematically compares the prediction performance of four types of surrogate models—POD-Linear, POD-Quadratic, POD-ANN, and End-to-End Encoder-Decoder—in both linear space and on the log manifold. Numerical results show that, after introducing log-manifold mapping, the average relative errors of all four models decrease significantly. Moreover, the trained surrogate models can achieve millisecond-level single-sample prediction, substantially reducing computational cost compared with high-fidelity SRW wave-optics simulations. These results indicate that log-manifold representation is a general improvement of the representation space suitable for surrogate modeling of high-dynamic-range radiation patterns, and can provide a technical route for rapid optical-field prediction, online optimization, and virtual diagnostics for future highly coherent accelerator light sources such as SSMB.

Keywords coherent accelerator light source; surrogate model; log manifold; SSMB; undulator radiation (3–6 terms)

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Log-Manifold Surrogate Modeling for Radiation Patterns from Coherent Accelerator Light Sources

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(SSMB) light sources, rapid and accurate optical-field prediction is increasingly important for beamline design, online optimization, and virtual diagnostics. However, high-accuracy wave-optics simulations are usually computationally expensive and difficult to use for real-time evaluation. In addition, coherent radiation patterns often exhibit high dynamic range and complex diffraction structures. Surrogate models constructed directly in the linear intensity space tend to be dominated by high-intensity regions, leading to insufficient accuracy in weak-intensity regions and edge diffraction structures. To address this issue, this work proposes a log-manifold-based End-to-End surrogate modeling framework for radiation patterns from high-coherence accelerator light sources. The non-negative intensity field is first mapped into the log-manifold, where surrogate modeling is performed, and the predicted result is then mapped back to the original linear space. Theoretical analysis shows that the Euclidean error in logarithmic space is first-order consistent with the relative error in the original intensity space, making the log-manifold representation more suitable for relative-error-oriented prediction of high-dynamic-range intensity fields. As a proof-of-concept study, SRW simulations of undulator radiation under fourth-generation synchrotron light source parameters are used as reference data. Four representative surrogate models, including POD-Linear, POD-Quadratic, POD-ANN, and an End-to-End Encoder-Decoder, are compared in both the linear intensity space and the log-manifold space. Numerical results show that the log-manifold mapping consistently reduces the mean relative error for all four surrogate models. The trained surrogate models achieve millisecond-level inference for a single sample, significantly reducing the computational cost compared with high-accuracy SRW simulations. These results indicate that the log-manifold representation is a general representation-space improvement for surrogate modeling of high-dynamic-range radiation patterns, and it provides a technical route for rapid optical-field prediction, online optimization, and virtual diagnostics in future SSMB and other high-coherence accelerator light sources.

Key words Coherence accelerator light source; Surrogate model; Log-manifold; SSMB; Undulator radiation

With the rapid development of fourth-generation synchrotron radiation light sources[^1–^5], accelerator light sources with high coherence, high brightness, and high stability have provided important support for cutting-edge scientific and engineering problems such as precision-structure detection, nanoscale imaging, and extreme-ultraviolet lithography. Advanced light-source schemes such as fourth-generation synchrotron radiation light sources and steady-state microbunching (Steady-State Microbunching, SSMB) light sources[^6,^7] have the potential to generate nearly fully coherent radiation and are becoming an important direction in the research of next-generation advanced light sources. Against this background, beamline design, commissioning, and operation often involve performance evaluation and optimization under multiple parameters, requiring a large number of computational tasks such as parameter scans, online optimization, and virtual diagnostics, which places higher demands on high-precision numerical simulation tools for beamlines.

For the simulation of beamlines in high-coherence accelerator light sources, academia and engineering fields have developed a series of high-precision wave-optics numerical simulation tools and theoretical methods. For example, simulation programs such as Synchrotron Radiation Workshop (SRW) can perform high-precision propagation-evolution calculations for the generation and wavefront propagation processes of synchrotron-radiation light sources, while propagation methods based on mutual optical intensity (Mutual Optical Intensity, MOI)[^8–^10] can describe diffraction effects and coherence properties relatively accurately. These methods can not only realize geometric ray tracing for various downstream optical elements starting from partially coherent synchrotron radiation generated in radiation elements (such as undulators), but also simulate high-precision, high-coherence diffraction fringe structures, thereby well preserving the wave-optical characteristics of the beam. However, numerical simulation methods based on full-wave propagation have extremely high computational costs and long single-simulation runtimes, making it difficult to meet engineering application requirements for real-time monitoring, rapid evaluation, and online feedback of beamlines. In recent years, by introducing coherent-mode decomposition[^11-^13], dimensionality reduction[^11-^13], Wigner functions[^14,^15], and parallel computing[^12], the computational-load problem of traditional coherent-optics simulation methods has been solved to some extent, partially satisfying the needs of offline simulation. However, for scenarios such as multi-parameter scans and online optimization, current simulation methods still cannot meet requirements.

To break through this computational bottleneck, surrogate models and machine-learning methods have gradually been introduced to replace complex numerical simulations[^16-^20]. However, because the partially coherent radiation spots generated by next-generation high-coherence light sources such as SSMB contain significant high-frequency diffraction structures, and because the intensity distribution between the center and the edges of the spot often spans several orders of magnitude, exhibiting an extremely large dynamic range, general models face very high difficulties and challenges in model performance and prediction quality when learning coherent optical-field distributions. These difficulties are not caused simply by insufficient model complexity, but are closely related to wave-optical characteristics such as the high spatial frequency and large dynamic range of the optical spot field itself in high-coherence accelerator light sources. Traditional models are mostly based on linear intensity space and 均

squared error (Mean Squared Error, MSE). During predictive reconstruction, it is very easily dominated by the central high-intensity region, causing the high-frequency weak diffraction fringe structures at the edges to be almost completely ignored or severely distorted, and it is not suitable for predicting coherent light sources. Therefore, for the wave-field propagation process of high-coherence light-source beams, the key to constructing a high-precision surrogate model lies not in model complexity, but in whether a representation space more suitable for characterizing complex diffraction structures can be found. This has become a major challenge that urgently needs to be solved in order to realize high-precision, high-fidelity surrogate modeling for synchrotron-radiation beamlines.

In response to the above problems, this paper addresses the need for rapid light-field prediction for high-coherence accelerator light sources such as SSMB, and proposes a surrogate modeling framework for high-dynamic-range synchrotron-radiation speckles based on a logarithmic manifold representation. This method recharacterizes nonnegative light-intensity fields from the perspective of representation space, maps the speckle distribution in the original linear space into a logarithmic manifold space, constructs a surrogate model in that space, and restores it to the original physical intensity space through inverse mapping. Theoretically, this paper analyzes the relationship between the logarithmic manifold mapping and relative error, showing that the Euclidean error in logarithmic space corresponds, under first-order approximation, to the relative error in the original intensity space, thereby making the learning space of the surrogate model consistent with the relative-error evaluation objective for high-dynamic-range intensity fields. In terms of numerical experiments, this paper uses fourth-generation light-source undulator radiation examples generated by SRW as the verification object, and systematically compares the prediction performance of four types of surrogate models—POD-Linear, POD-Quadratic, POD-ANN, and End-to-End Encoder-Decoder—in the original linear space and in the logarithmic manifold space. The results show that logarithmic manifold mapping can stably reduce the mean relative error in surrogate models of different complexity, and can achieve rapid speckle prediction at millisecond-scale inference times, providing a feasible technical route for rapid parameter scanning, online optimization, and virtual diagnostics of high-coherence accelerator light sources such as SSMB in the future.

1 Surrogate Modeling Method Based on the Logarithmic Manifold

1.1 Logarithmic Manifold Mapping

Speckles from high-coherence accelerator light-source radiation usually have such characteristics as nonnegativity, high dynamic range, and complex diffraction fringe structures. If a surrogate model is constructed directly in the original linear space, the central high-intensity region will occupy a dominant position in the mean-squared-error training objective, while the errors of the weak-intensity diffraction fringe structures at the edges are difficult to constrain sufficiently. Therefore, the key to building a surrogate model for high-coherence radiation in the original linear space lies not only in increasing the complexity of the model itself, but also in selecting a representation space that matches the error characteristics of high-dynamic-range intensity fields.

To solve this problem, we propose a logarithmic manifold mapping method that re-represents the speckle intensity distribution in logarithmic space. This mapping can not only greatly compress the high-dynamic-variation range of the light field so as to facilitate the construction of a surrogate model, but also makes the construction error of the surrogate model theoretically equivalent to minimizing the relative error in the original linear space, greatly improving the performance of the surrogate model in high-coherence simulation scenarios.

1.1.1 Logarithmic Mapping of the Positive Intensity Field

Let the light-intensity distribution at a point on the beamline of a high-coherence accelerator light source be:

$$I(x;\mu) > 0, x = (x, y). \qquad (1)$$

where x is the spatial position and μ is the beamline or light-source parameter configuration. Since light intensity is a nonnegative physical quantity, it can be defined as an element in the positive space. Meanwhile, to avoid numerical divergence caused by zero-intensity points, we introduce a small positive number ε, and define the logarithmic manifold mapping as:

$$T : I(x; \mu) \mapsto L(x; \mu) = log(I(x; \mu) + \varepsilon), \varepsilon \ll 1. \qquad (2)$$

Its inverse mapping is:

$$T^{-1} : L(x; \mu) \mapsto I(x; \mu) = exp(L(x; \mu)) - \varepsilon. \qquad (3)$$

From a numerical perspective, logarithmic manifold mapping first significantly compresses the dynamic range of speckles. For the intensity distributions spanning several orders of magnitude that commonly exist in high-coherence radiation speckles, the extremely large intensity differences in the linear intensity space are converted into approximately linear scales in the logarithmic space, thereby avoiding the dominance of local bright regions in the MSE error and allowing weak-intensity regions and edge diffraction structures to receive more balanced weights during surrogate-model construction.

Therefore, logarithmic mapping not only greatly improves the representability of high-coherence radiation speckles, but also significantly linearizes high-frequency diffraction structures, transforming the originally highly nonlinear intensity distribution into a more learnable manifold structure.

1.1.2 Relative error indicators and logarithmic-flow manifold geometry

The indicators used to evaluate surrogate models should not consist solely of absolute error. For a coherent synchrotron radiation light-intensity field with a large dynamic range, relative error can better reflect the prediction quality in weak-intensity regions and at the edges of diffraction structures than absolute error. The following analysis shows that the error of a surrogate model constructed on the logarithmic-flow manifold has a first-order equivalence relation with the relative error in the original linear space.

Let the prediction result of the surrogate model be $\hat{I}(x)$, and the true light-intensity field be $I(x)$. Define the pointwise relative error as:

$$r(x) = \frac{\hat{I}(x) - I(x)}{I(x)}. \qquad (4)$$

When $I(x) > 0$ and the relative error is small, we have:

$$log\,\hat{I}(x) - log\,I(x) = log\left(\frac{\hat{I}(x)}{I(x)}\right) = log(1 + r(x)) \approx r(x). \qquad (5)$$

Considering the small quantity ε used in actual numerical computations to avoid zero intensity, the logarithmic-flow mapping can be written as:

$$L(x) = log(I(x) + \varepsilon). \qquad (6)$$

On the logarithmic-flow manifold, the prediction error satisfies:

$$\hat{L}(x) - L(x) = log(\hat{I}(x) + \varepsilon) - log(I(x) + \varepsilon). \qquad (7)$$

When the deviation is sufficiently small, we have

$$\hat{L}(x) - L(x) \approx \frac{\hat{I}(x) - I(x)}{I(x) + \varepsilon}. \qquad (8)$$

At this point, the mean-square error in logarithmic space can be approximated as

$$\left\|\hat{L} - L\right\|_2^2 = \int \left(\frac{\hat{I}(x) - I(x)}{I(x) + \varepsilon}\right)^2 dx. \qquad (9)$$

The above formula indicates that minimizing the Euclidean error in logarithmic space is approximately equivalent to minimizing the squared relative error in the original linear space. In contrast, if the mean-square error is minimized directly in the linear intensity space, then:

$$\left\|\hat{I} - I\right\|_2^2 = \int (\hat{I}(x) - I(x))^2 dx = \int (I(x) + \varepsilon)^2 \left(\frac{\hat{I}(x) - I(x)}{I(x) + \varepsilon}\right)^2 dx. \qquad (10)$$

This means that, in the original linear space, the central high-intensity region receives a larger weight, while the error contribution from weak-intensity regions and diffraction structures at the edges is significantly weakened. For coherent synchrotron radiation speckles with a large dynamic range, such nonuniform weighting causes the surrogate model to be dominated more by the central high-brightness region, making it difficult to accurately predict the weak diffraction fringe structures at the edges.

From the perspective of manifold geometry, the logarithmic-flow mapping can be understood as introducing a metric on the positive intensity field to characterize relative changes. Let the space composed of all light-intensity fields satisfying the positivity condition be:

$$\mathcal{M} = \{I(x) \mid I(x) > 0\}. \qquad (11)$$

Define the logarithmic-flow mapping:

$$\Phi : \mathcal{M} \to L^2, \Phi(I) = log(I(x) + \varepsilon). \qquad (12)$$

For two tangent perturbations $u(x)$ and $v(x)$ at $I \in \mathcal{M}$, the differential of the mapping Φ is:

$$D\Phi_I[u] = \frac{u(x)}{I(x) + \varepsilon}. \qquad (13)$$

Therefore, the Riemannian metric induced by the logarithmic mapping is

$$g_I(u, v) = \langle D\Phi_I[u], D\Phi_I[v] \rangle_{L^2} = \int \frac{u(x)v(x)}{(I(x) + \varepsilon)^2}\, dx. \qquad (14)$$

Correspondingly, the length of an infinitesimal perturbation dI of the intensity under this metric satisfies

$$ds^2 = g_I(dI, dI) = \int \left(\frac{dI(x)}{I(x) + \varepsilon} \right)^2 dx. \qquad (15)$$

The above equation shows that what the Riemannian distance measures on the logarithmic manifold is relative change,

$$\frac{dI(x)}{I(x) + \varepsilon}. \qquad (16)$$

rather than absolute change dI. Thus, the logarithmic manifold naturally corresponds mathematically to a relative-error metric.

Furthermore, we consider geodesics on the logarithmic manifold. A geodesic gives the shortest path between two samples on the manifold. For any curve $\gamma(t)$ connecting I_0 and I_1, where $t \in [0, 1]$, $\gamma(0) = I_0$, and $\gamma(1) = I_1$, its length under the above Riemannian metric [21–23] is

$$L(\gamma) = \int_0^1 \sqrt{g_\gamma(\dot{\gamma}(t), \dot{\gamma}(t))}\, dt. \qquad (17)$$

Since the logarithmic mapping $\Phi(I) = log(I + \varepsilon)$ maps the positive-valued intensity field to the linear Hilbert space L^2, on the logarithmic manifold, the geodesic between two samples is the straight line in L^2 space. Let

$$L_0 = log(I_0 + \varepsilon), \quad L_1 = log(I_1 + \varepsilon). \tag{18}$$

Then the geodesic path in logarithmic space is

$$L(t) = (1 - t)L_0 + tL_1. \tag{19}$$

Mapping it back to the original intensity space through the inverse mapping yields the geodesic on the logarithmic manifold in the original linear space:

$$\gamma(t) = exp[(1-t)\, log(I_0+\varepsilon)+t\, log(I_1+\varepsilon)]-\varepsilon = (I_0+\varepsilon)^{1-t}(I_1+\varepsilon)^t-\varepsilon. \tag{20}$$

This shows that the geodesic on the logarithmic manifold corresponds in the original intensity space to a pointwise geometric-mean path, rather than to the arithmetic-mean path in the linear intensity space. From the perspective of surrogate modeling, the prediction process is essentially learning the continuous mapping relationship between different intensity-field samples in parameter space. If a surrogate model is constructed directly in the linear intensity space, the model implicitly approximates the intensity field under Euclidean geometry, that is, it performs interpolation and extrapolation along linear paths in the sense of absolute error. This geometry will cause the high-intensity regions to dominate the fitting direction of the model, and therefore it may not necessarily correspond to the optimal prediction path in the sense of relative error.

When constructing a surrogate model on the logarithmic manifold, because the Hilbert space on the logarithmic manifold is linear, the surrogate model, during interpolation or regression, predicts along the geodesics of the logarithmic manifold in the original intensity space. At this point, the surrogate model is not predicting samples in the sense of absolute intensity, but rather in the sense of a relative-error metric. Therefore, for the prediction task of high-coherence light-source radiation spots in which relative error is the principal evaluation metric, the logarithmic manifold provides a more natural surrogate-model representation space than the original linear space.

1.2 Surrogate Model Method

After completing the logarithmic-manifold mapping, the surrogate model needs to learn, in the selected representation space, from the ray and light-source parameter configuration to the two-dimensional same-mapping relationship among speckle patterns. Let the beam line and light-source parameter configuration vector be μ, and denote the two-dimensional light-intensity distribution as

$$I(x;\mu) > 0, x = (x, y). \qquad (21)$$

The objective of the surrogate model is to learn the mapping from the parameter space to the light-intensity space,

$$\mu \mapsto I(x;\mu). \qquad (22)$$

To accurately reconstruct the overall morphology and local fringe structures of speckle patterns radiated by highly coherent light sources, this paper adopts an end-to-end model based on Encoder–Decoder as the principal surrogate-model method. This model directly learns the nonlinear mapping relationship between the input parameters and the two-dimensional logarithmic light-intensity field, and is more suitable for describing the spatial structure of complex radiation speckles.

At the same time, in order to verify whether the role of the logarithmic-flow representation has model universality, rather than relying only on a certain neural-network architecture, this paper further introduces three surrogate-model methods based on a linear orthogonal subspace and POD coefficient regression —POD-Linear, POD-Quadratic, and POD-ANN—as comparisons. The three methods correspond respectively to linear response surfaces, quadratic response surfaces [24,25], and neural-network nonlinear regression, covering different levels of complexity from traditional low-order dimensionality-reduction surrogate models to nonlinear dimensionality-reduction surrogate models. Through this setup, the effect of logarithmic-flow representation in different types of surrogate models can be systematically evaluated.

1.2.1 End-to-End Encoder-Decoder

The End-to-End Encoder-Decoder surrogate model directly learns the mapping relationship from the input parameter vector to the two-dimensional light-intensity field distribution. This method does not explicitly construct a linear modal space, but instead directly learns the nonlinear relationship between the parameter space and the two-dimensional optical-field space through a neural network [26,27].

In the logarithmic flow, the network learning objective can be expressed as:

$$\hat{J}(x;\mu) = G_\theta(\mu), \qquad (23)$$

where G_θ is the input-parameter encoding and image-decoding network. Specifically, the input parameters are first mapped by the encoder into a latent-space vector:

$$z = E_\theta(\mu), \qquad (24)$$

after which the latent-space vector is upsampled layer by layer through the decoder, ultimately yielding the predicted result for the two-dimensional optical field:

$$\hat{J}(x;\mu) = D_\theta(z). \qquad (25)$$

Therefore, the entire end-to-end Encoder-Decoder surrogate model can be expressed as:

$$\hat{J}(x;\mu) = D_\theta(E_\theta(\mu)). \qquad (26)$$

The training objective of this model is the mean squared error in image space:

$$\mathcal{L}_{mse} = \frac{1}{N}\sum_{i=1}^{N}\left\|G_\theta(\mu_i) - J_i\right\|_2^2. \qquad (27)$$

The End-to-End Encoder-Decoder surrogate-model method does not depend on preconstructed POD modes and is not constrained by the assumptions of a linear orthogonal subspace. In theory, it has stronger nonlinear expressive capability and can directly learn the complex mapping relationship between the input parameters and the light-intensity field. For prediction tasks involving highly coherent radiation speckles that contain complex spatial fringes and high-dynamic-range structures, the Encoder-Decoder model can learn speckle features in the latent-space representation and recover the two-dimensional spatial structure through the decoder. Therefore, this paper uses this model as the principal end-to-end two-dimensional optical-field prediction framework, to verify the effectiveness of logarithmic-flow representation in complex nonlinear surrogate models.

1.2.2 Surrogate Modeling Methods Based on POD Bases

To further verify the universality of logarithmic-flow representation for different surrogate modeling methods, this paper introduces three types of surrogate models based on POD coefficient regression for comparison, namely POD-Linear, POD-Quadratic, and POD-ANN. All three models use the same POD linear subspace dimensionality-reduction representation; they differ only in the regression model from the input parameters to the POD coefficients.

Taking the logarithmic-flow space as an example, suppose the light-intensity distribution of the i-th sample is

$$L_i(x) = log(I_i(x) + \varepsilon), \qquad (28)$$

and the mean field is

$$\bar{L}(x) = \frac{1}{N}\sum_{i=1}^{N} I_i(x) \qquad (28)$$

where N is the number of samples in the training set. Performing POD decomposition on the decentered training set [28], a set of eigen-orthogonal bases $\{\phi_k(x)\}_{k=1}^{r}$ can be obtained. Thus, any sample can be expanded on this basis as

$$L_i(x) \approx \bar{L}(x) + \sum_{k=1}^{r} \alpha_{ik}\phi_k(x), \qquad (29)$$

where r is the number of retained POD modes, and α_{ik} is the coefficient of the i-th sample on the k-th POD mode. Denote the POD coefficient vector as

$$\alpha_i = (\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{ir})^T. \qquad (30)$$

Therefore, the POD-based surrogate modeling problem can be transformed into learning the mapping between the input parameters and the POD coefficients:

$$\mu \mapsto \alpha(\mu). \qquad (31)$$

This paper adopts three regression methods with different complexities to construct surrogate models:

$$\mathcal{R}(\mu) = \begin{cases} W\mu + b, & POD - Linear \\ Cp_2(\mu), & POD - Quadratic, \\ \mathcal{N}_\theta(\mu), & POD - ANN \end{cases} \qquad (32)$$

where, in POD-Linear, it is assumed that the input parameters and POD coefficients satisfy a linear relationship, with $W \in \mathbb{R}^{r\times d}$ being the linear mapping matrix and $b \in \mathbb{R}^r$ the bias term. This method has few parameters, fast reconstruction speed, simple coefficient fitting, and strong interpretability, and is suitable as a conventional low-complexity surrogate-model baseline.

POD-Quadratic further introduces quadratic terms and interaction terms on the basis of POD-Linear, for representing the quadratic nonlinear relationship between the input parameters and the POD coefficients. Suppose that for a three-dimensional input parameter

$$\mu = (\mu_1, \mu_2, \mu_3), \qquad (33)$$

the quadratic polynomial feature vector is constructed as

$$p_2(\mu) = [1, \mu_1, \mu_2, \mu_3, \mu_1^2, \mu_2^2, \mu_3^2, \mu_1\mu_2, \mu_1\mu_3, \mu_2\mu_3]^T. \qquad (34)$$

The quadratic response surface of the POD coefficients [29,30] can be approximately expressed as

$$\alpha(\mu) = Cp_2(\mu), \qquad (35)$$

where $C \in \mathbb{R}^{r\times m}$ is the coefficient of the quadratic response surface to be fitted. Compared with POD-Linear, this method has better nonlinear expressive capability while maintaining relatively low fitting complexity and computational cost.

The POD-ANN method replaces linear or quadratic response-surface fitting by training a neural-network model, so as to learn the more complex nonlinear relationship between the input parameters and the light field. It can be expressed as:

$$\alpha(\mu) = \mathcal{N}_\theta(\mu). \qquad (36)$$

Here, $\mathcal{N}_\theta(\mu)$ denotes the neural-network model with parameters θ. Compared with the two methods described above, POD-ANN no longer assumes a linear or quadratic relationship between the input parameters and the light-intensity field, but instead directly learns the more complex nonlinear mapping between the two by training a neural-network model.

For the above three surrogate models based on POD coefficient fitting/regression, after predicting $\hat{\alpha}(\mu)$, the logarithmic light-intensity field can be reconstructed through the POD modes:

$$\hat{L}(x;\mu) \approx \bar{L}(x;\mu) + \sum_{k=1}^{r} \hat{\alpha}_k \phi_k(x;\mu). \qquad (37)$$

It is then restored to the original linear space through the inverse logarithmic mapping:

$$\hat{I}(x;\mu) = exp(L(x;\mu)) - \varepsilon. \qquad (38)$$

These three types of POD coefficient regression models together constitute a comparison model group ranging from simple to complex. Among them, POD-Linear is used to test the performance of the least-complex linear model; POD-Quadratic is used to evaluate whether a traditional quadratic response surface can describe the nonlinear effects caused by parameter variation; and POD-ANN is used to test whether, under the condition of a stronger nonlinear regressor, the logarithmic-flow representation can still bring improvements in prediction accuracy. By comparison with an End-to-End Encoder-Decoder, it is possible to further determine whether the effectiveness of the logarithmic-flow representation is model-independent.

1.3 Overall framework of the surrogate-model method based on logarithmic flow

Based on the aforementioned logarithmic-flow mapping and surrogate-model methods, this paper constructs a unified surrogate-modeling framework for logarithmic flow. The core idea of this framework is as follows: instead of directly learning the light-intensity field in the original linear space, first map the high-dynamic-range partially coherent synchrotron radiation speckle pattern into the logarithmic-flow space, complete surrogate-model prediction in that space, and finally restore it to the original physical intensity space through the inverse mapping.

For a given beamline or light-source parameter configuration μ, the light-intensity field distribution obtained from high-fidelity simulation is denoted as $I(x;\mu)$. First, apply the logarithmic mapping to it:

$$L(x;\mu) = log(I(x;\mu) + \varepsilon). \qquad (39)$$

Subsequently, construct a surrogate model on the logarithmic flow:

$$g_\theta : \mu \mapsto \hat{L}(x;\mu). \qquad (40)$$

Here, g_θ can be implemented using different surrogate models, including POD-Linear, POD-Quadratic, POD-ANN, and an End-to-End Encoder-Decoder. For the proper orthogonal decomposition type of method, the surrogate model predicts a low-dimensional representation in the logarithmic space; for the end-to-end model, the surrogate model directly predicts the two-dimensional logarithmic light-intensity field. The specific forms of the different models have been given in Section 2.2.

After completing prediction in the logarithmic space, restore it to the original linear space through the inverse mapping:

$$\hat{I}(x;\mu) = exp(\hat{L}(x;\mu)) - \varepsilon. \qquad (41)$$

Log Manifold Surrogate Model Framework

Figure 1: Log Manifold Surrogate Model Framework

Finally, evaluation indicators such as the mean relative error are calculated in the original linear space. From Section 2.1, it is known that the Euclidean error on the logarithmic flow is, under a first-order approximation, equivalent to the relative error in the original linear space; therefore, this framework can make the representation space used to construct the surrogate model consistent with the error evaluation indicator of final concern.

In summary, the overall workflow of the method proposed in this paper can be summarized as follows:

$$I(\mathbf{x};\mu) \to L(\mathbf{x};\mu) \to g_\theta \to \hat{L}(\mathbf{x};\mu) \to \hat{I}(\mathbf{x};\mu)$$

By applying a logarithmic-manifold mapping to radiation light fields with a high dynamic range, this framework provides a more natural representation-learning space for different types of surrogate models whose primary evaluation metric is relative error. Figure 1 presents the overall workflow of the log-manifold surrogate-modeling method proposed in this paper.

Figure 1 Overall framework of the log-manifold-learning-based surrogate model method for radiation from a high-coherence accelerator light source

Fig.1 Overall framework of the log-manifold-learning-based surrogate model for high-coherence accelerator light source radiation

2 Numerical Experiments and Results Analysis

2.1 Numerical Experiment Setup

To verify the effectiveness of the proposed log-manifold surrogate-model framework, this paper constructs a numerical experimental dataset based on the synchrotron-radiation wave-optics simulation software SRW, and systematically compares the prediction results of different surrogate models in the original linear space and in the logarithmic-manifold space. This chapter first introduces the SRW undulator-radiation example, the dataset construction method, and the surrogate-model configurations; it then analyzes the influence of logarithmic-manifold mapping on surrogate-model prediction accuracy from two aspects: sample-level error statistics and spot-reconstruction results; finally, it further discusses the potential value of this method in computational efficiency and engineering applications.

2.1.1 Construction of the Numerical Experimental Dataset All numerical experimental data used in this paper are generated based on the synchrotron-radiation wave-optics simulation software SRW. SRW adopts rigorous wave-optics theory to perform full-wave numerical calculations of undulator radiation during emission in the insertion device and subsequent propagation along the beamline. It can accurately describe the wave-optical effects of the light field under high-coherence conditions and has been widely used in the design and performance evaluation of synchrotron-radiation beamlines. Therefore, data generated by SRW can be regarded as high-fidelity reference solutions for the training and validation of surrogate models.

This paper uses the reconstruction prediction of the radiation spot from an undulator under fourth-generation light-source parameters as the validation example. This example does not involve the complete propagation process through complex beamline elements, but mainly focuses on the prediction problem of the two-dimensional intensity distribution of undulator radiation on the observation plane. The purpose of this setup is to eliminate the influence of details of complex engineering beamlines and to focus on verifying the effectiveness of logarithmic-manifold representation for surrogate modeling of nonnegative, high-dynamic-range radiation fields from fourth-generation synchrotron-radiation sources and future SSMB sources.

In the SRW simulation, the undulator period length is $0.033m$, the number of periods is 70, the electron-beam energy is $6GeV$, and the average current is $0.1A$. The dataset adjusts the undulator strength K by scanning the vertical magnetic-field strength B_y of the undulator. To control variables, all surrogate models in both the original linear space and the logarithmic-manifold space use the same dataset reading method, center-cropping method, training/test-set split method, and error-evaluation metrics. Table 1 lists the main physical parameters of the SRW undulator-radiation example used in this paper.

Fig. 2 Schematic beamline configuration for wavefront propagation from undulator radiation

Table 1 Detailed parameters of SRW simulation

Category	Parameter	Value	Unit
Undulator	Period length	0.033	m
Undulator	Number of periods	70	–
Undulator	Vertical magnetic-field amplitude B_y	0.7–1.1	T
Undulator	Vertical magnetic-field amplitude B_x	0.0	T
Electron beam	Average current	0.1	A
Electron beam	Electron energy	6	GeV
Electron beam	Relative energy spread	0.11%	–

Category	Parameter	Value	Unit
Electron beam	Horizontal beam size σ_x	20	μm
Electron beam	Horizontal beam divergence σ'_x	2	μrad
Electron beam	Vertical beam size σ_y	2	μm
Electron beam	Vertical beam divergence σ'_y	0.5	μrad

2.1.2 Surrogate-model configuration and evaluation metrics

To verify the influence of log-flow mapping on the prediction results of different surrogate models, this paper selects four representative surrogate models for comparison, including POD-Linear, POD-Quadratic, POD-ANN, and End-to-End Encoder-Decode. Among them, POD-Linear and POD-Quadratic represent conventional first-order and second-order response-surface surrogate models, respectively; POD-ANN represents a nonlinear neural-network surrogate model based on dimensionality reduction by proper orthogonal decomposition; and End-to-End Encoder-Decoder represents an end-to-end two-dimensional field prediction model based on an encoder–decoder.

Each type of surrogate model is constructed and used for prediction separately in the original linear space and in the log-flow space. Through comparative experiments, the influence of the log-flow mapping method itself on the modeling accuracy of surrogate models can be reflected. The specific surrogate-model settings are shown in Table 2.

Table 2 Comparison of Surrogate model experimental setups

Surrogate-model category	Representation space	Prediction target	Surrogate-model form
POD-Linear	Linear/Log	POD coefficients	First-order polynomial response surface
POD-Quadratic	Linear/Log	POD coefficients	Second-order polynomial response surface
POD-ANN	Linear/Log	POD coefficients	Multilayer perceptron MLP
End-to-End	Linear/Log	Two-dimensional light-intensity field	Encoder-Decoder

For the neural-network models, POD-ANN uses a multilayer fully connected network to train on the POD coefficients and predict the reconstruction; End-to-End Encoder-Decoder directly learns the mapping from input parameters to the two-dimensional light-intensity field. The specific network hyperparameters are shown in Table 3.

Table 3 Neural networks and training hyperparameters

Surrogate-model category	Epoches	Batch size	Learning rate	Hidden-layer dimension	Network depth	Latent-space dimension	Optimizer
POD-ANN	Linear/Log	64	1×10^{-3}	512	8	–	Adam/AdamW
End-to-End	Linear/Log	8	1×10^{-3}	512	–	256	Adam/AdamW

In this paper, the mean relative error (Mean Relative Error, MRE) is adopted as the primary evaluation metric. To avoid metric calculation in the weak-field region

Because the denominator is extremely small, leading to numerical instability, this paper adds a small quantity ε to the relative-error denominator to stabilize the calculation of the mean relative error metric. The sample-wise mean relative error is defined as:

$$MRE = \frac{1}{N}\sum_{j=1}^{N}\frac{|\hat{I}_j - I_j|}{I_j + \varepsilon}. \qquad (42)$$

Here, $\hat{I}_j$ and I_j denote, respectively, the optical intensity predicted by the surrogate model and the SRW reference optical intensity at the j-th image pixel, and N is the total number of image pixels. This metric can effectively reflect the relative prediction accuracy of the surrogate model over the full dynamic range, and is particularly suitable for evaluating the reconstruction performance in weak-intensity regions and edge diffraction structures.

2.2 Results and error analysis of spot reconstruction under logarithmic-flow mapping

2.2.1 Analysis of error statistics

First, the sample-wise mean relative errors of the four surrogate models in the original linear space and in the logarithmic-flow space are computed. Figure 3 presents the error distribution results of different surrogate models under the two settings of linear (no-log) and with-log. It can be seen that, for the four models –POD-Linear, POD-Quadratic, POD-ANN, and End-to-End Encoder-Decoder –the distributions of the mean relative errors all decrease markedly after introducing logarithmic-flow mapping. This indicates that the error improvement brought by logarithmic mapping does not depend on a particular surrogate-model structure, but comes from the change in the representation space of the high-dynamic-range synchrotron-radiation intensity field.

From the comparison among different models, POD-Linear has the lowest model complexity, and therefore its error in the linear intensity space is relatively large; after logarithmic mapping is added, its error distribution decreases significantly, showing that logarithmic flow can markedly improve the learnability of low-order linear surrogate models. POD-Quadratic has stronger nonlinear expressive capability after the introduction of quadratic terms, and its overall error is lower than that of POD-Linear; nevertheless, logarithmic mapping further reduces the error level. For POD-ANN and the End-to-End Encoder-Decoder, even though the models themselves have relatively strong nonlinear expressive capability, the logarithmic-flow representation still brings stable improvement, indicating that this method not only compensates for low-order models, but can also improve the consistency between the training objectives and error evaluation of neural-network surrogate models.

To further quantify the improvement effect of logarithmic mapping, Table 4 summarizes the mean relative errors of different surrogate models on the training set, interpolation test set, and all samples. The table also gives the results under the two settings of linear (no-log) and with-log, as well as the error reduction ratios.

Fig. 3 Sample-wise MRE distributions and error reduction rates of different surrogate models with and without log mapping

Table 4 Comparison of mean relative errors for different surrogate models

Model	Representation space	Train MRE/%	Interp MRE/%	All MRE/%	Median MRE/%	Error reduction ratio/%
POD-Linear	Linear	25.26	26.78	26.63	23.21	–

Method	Space	Value 1	Value 2	Value 3	Value 4	Value 5
POD-Linear	Log	13.57	14.11	14.06	14.34	47.2
POD-Linear	Linear	12.91	13.46	13.41	12.6	–
POD-Quadratic	Log	10.44	11.41	11.31	11.13	15.64
POD-Quadratic	Linear	8.32	9.48	9.36	7.7	–

Fig. 4 Spot prediction results and relative error distributions of the log-manifold-based surrogate model on the test sets

Figure 2: Fig. 4 Spot prediction results and relative error distributions of the log-manifold-based surrogate model on the test sets

Method	Space	Value 1	Value 2	Value 3	Value 4	Value 5
POD-ANN	Log	2.71	4.71	4.51	3.24	51.8
POD-ANN	Linear	9.42	10.39	10.29	9.27	–
End-to-End	Log	3.59	5.28	5.11	4.01	50.35

2.2.2 Analysis of Spot Reconstruction Results

To further analyze the surrogate models' ability to reconstruct two-dimensional spot structures, Fig. 4 presents the spot prediction results and relative error distributions on representative test samples. The figure shows the SRW high-fidelity simulation results, the prediction results of the surrogate models in the original linear space and in the logarithmic manifold space, respectively, as well as the corresponding relative error maps.

From the original light-intensity distribution, it can be seen that the undulator radiation spot calculated by SRW has an obvious high dynamic range and strong diffraction-fringe characteristics; there is a relatively large amplitude difference between the central high-intensity region and the weak-intensity regions at the edges. Surrogate models trained in the original linear space are more easily dominated by the central high-intensity region, and their learning of the weak-intensity regions and edge diffraction-fringe structures is insufficient. By contrast, surrogate models in the logarithmic manifold space can more evenly reconstruct the main peak region and weak-intensity regions, showing better stability in the overall spot morphology, main-peak position, and edge-region structures.

The relative error distributions further show that the logarithmic-manifold representation can effectively reduce the numerical imbalance caused by the high dynamic range. Compared with predictions in the linear space, the high-error regions in the predictions on the logarithmic manifold are significantly reduced, and the error distribution is more uniform. This is consistent with the sample-level error statistics in the previous section, indicating that the logarithmic mapping not only improves the average error, but also enhances the accuracy and stability of two-dimensional light-intensity-field reconstruction.

Fig.4 Spot prediction results and relative error distributions of the log-manifold-based surrogate model on the test sets

2.3 Analysis of Method Effectiveness and Engineering Significance

Combining the above numerical experimental results, it can be seen that the surrogate modeling method based on the logarithmic-manifold representation can greatly improve the predictive performance of surrogate models for radiation spots from high-coherence accelerator light sources. Compared with directly constructing surrogate models in the original linear space, the logarithmic-manifold representation can compress the dynamic range of light intensity, so that the model training process is no longer excessively dominated by the central high-intensity region, thereby better accounting for the relative errors in weak-intensity regions and edge diffraction-fringe structures. More importantly, this improvement can be observed across multiple types of surrogate models, indicating that logarithmic mapping is not an empirical technique tied to a specific surrogate model, but a general improvement of the representation space for nonnegative, high-dynamic-range light-intensity fields.

In terms of prediction accuracy, POD-ANN (with-log) achieves the lowest average relative error on the current dataset, with an All MRE of 4.51% and a Median MRE of 3.24%. End-to-End (with-log) has an All MRE of 5.11% and a Median MRE of 4.01%, also demonstrating good predictive capability. By comparison, although traditional polynomial models have faster training and inference speeds, their error levels are relatively high due to limitations in model expressiveness. Among them, POD-Linear (with-log) has an All MRE of 14.06%, and POD-Quadratic (with-log) has an All MRE of 11.31%. This shows that, in the present validation example, the combination of POD-ANN and the logarithmic-manifold representation achieves a better balance between accuracy and computational cost; the End-to-End model provides an extensible path for nonlinear-field prediction on more complex datasets in the future.

In terms of computational efficiency, SRW high-fidelity simulation requires multi-electron statistical synchrotron radiation calculations, and a single simulation usually has relatively high computational cost.

Compared with this, after training is completed, the surrogate model needs to execute only one rapid prediction to obtain the two-dimensional light-intensity field corresponding to the input parameters. Table 5 summarizes the training time of different surrogate models, the prediction time for a single sample, and the speedup relative to the SRW reference time. Here, a single multi-electron SRW simulation time of half an hour is used as the reference time to estimate the speedup of surrogate-model inference.

As can be seen from Fig. 5, the single-sample prediction times of all surrogate models are at the millisecond level. The POD-ANN method has the fastest inference speed: the single-sample prediction time of the linear-space surrogate model is only 1.56 ms, and the prediction time on the logarithmic flow shape is 3.03 ms. Overall, all surrogate models achieve a speedup of $10^5 \sim 10^6$ relative to the half-hour SRW reference computation time.

Fig. 5 Comparison of computational efficiency for different surrogate models

Figure 3: Fig. 5 Comparison of computational efficiency for different surrogate models

In terms of training cost, the fitting-coefficient computation times of the traditional surrogate-model methods POD-Linear and POD-Quadratic are both less than 1 s, whereas the training time of POD-ANN is about 43–45 s. Because the End-to-End model directly predicts two-dimensional image fields, its training time increases significantly, to about 27–28 min. The above results show that different surrogate-model methods are suitable for problems of different complexity: the POD-Linear and POD-Quadratic methods are simple in form and highly interpretable, and are suitable for rapid prediction scenarios in which, under low-dimensional parameters, the light spot exhibits weak nonlinearity as the light source and beamline configurations change; POD-ANN, based on a neural-network model, further enhances the fitting capability for nonlinear coefficients, and is more suitable for tasks such as wave-undulator radiation examples, where the sample size is limited and the parameter dimension is relatively low, yet high prediction accuracy is still required. By contrast, the End-to-End Encoder-Decoder does not rely on a preset linear subspace and can directly learn the nonlinear mapping from input parameters to the two-dimensional optical field, making it more suitable for future modeling requirements involving complex beamline configurations, high-dimensional parameter spaces, and end-to-end digital twins in highly coherent accelerator light sources such as SSMB. Therefore, although in the current example POD-ANN (with-log) performs best in terms of accuracy and efficiency, End-to-End (with-log) remains a principal surrogate-model approach with greater potential for complex SSMB optical-field prediction tasks.

Fig. 5 Comparison of computational efficiency for different surrogate models

Table 5 Comparison of prediction error and computational efficiency for different surrogate models

Model	Representation space	Mean MRE / %	Training time / s	Single inference time / ms	Speedup relative to SRW
POD-Linear	Linear	26.63	0.85	10.52	1.71×10^5
POD-Linear	Log	14.06	0.75	16.23	1.11×10^5
POD-Quadratic	Linear	13.41	0.85	8.79	2.05×10^5
POD-Quadratic	Log	11.31	0.74	14.76	1.22×10^5

Model	Representation space	Mean MRE / %	Training time / s	Single inference time / ms	Speedup relative to SRW
POD-ANN	Linear	9.36	45.07	1.56	1.15×10^6
POD-ANN	Log	4.51	43.52	3.03	5.94×10^5
End-to-End	Linear	10.29	1631.21	2.83	6.37×10^5
End-to-End	Log	5.11	1672.18	5.77	3.12×10^5
SRW	–	–	–	1.8×10^6	1

3 Conclusion

For the problem of the high numerical-simulation cost of high-coherence accelerator light sources such as fourth-generation synchrotron radiation light sources and steady-state microbunching (SSMB), ···

problem, this paper proposes a high-dynamic-range synchrotron-radiation light-field surrogate modeling framework based on logarithmic-streamflow representation. By mapping the non-negative light-intensity field from linear space to logarithmic-streamflow space, this method effectively overcomes the prediction-error bottleneck of traditional surrogate models, which are easily dominated by the central high-intensity region and find it difficult to simultaneously account for the weak fringes of edge diffraction.

Numerical experiments take the SRW wiggler radiation spot as a validation example, and verify the universality of this framework on multiple classes of surrogate models (POD-Linear, POD-Quadratic, POD-ANN, and End-to-End Encoder-Decoder). The results show that, after introducing the logarithmic-streamflow mapping, the prediction accuracy of all types of models is significantly improved. Among them, the POD-ANN model combined with logarithmic streamflow performs best: it reduces the overall mean relative error to 4.51% (median error 3.24%), and the single-sample inference time is only at the millisecond level, achieving an optimal balance between accuracy and computational efficiency. In addition, the End-to-End logarithmic-streamflow method does not depend on a preset linear subspace, and can directly learn the nonlinear mapping relationship from input parameters to the two-dimensional light field. It is more consistent with the future requirements of end-to-end surrogate-model prediction under complex beamline configurations and high-dimensional parameter spaces for highly coherent accelerator light sources such as SSMB, and is an important direction for subsequent methodological expansion.

Overall, this study shows that the key to constructing high-accuracy, high-dynamic-range optical-field surrogate models lies not only in increasing the complexity of the surrogate model, but also in selecting a representation space corresponding to the error characteristics of the target physical field. The logarithmic-streamflow framework proposed in this paper provides an effective path for rapid and high-accuracy prediction of spots from highly coherent accelerator light sources. Future work will further extend it to realistic SSMB radiation conditions, including full wavefront propagation of complex beamline elements, multi-energy-spectrum inputs, and higher-dimensional parameter spaces, with the aim of realizing practical application value in beamline digital twins, virtual diagnostics, and online optimization.

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Author Contributions Statement

All authors participated in the theoretical and design work of the study. Song Xuanying was responsible for scheme design, theoretical derivation, numerical experiment implementation, and manuscript writing; Sun Jiarui participated in scheme design, numerical-result analysis, and manuscript revision; Hu Jun and Hu Haowei participated in model training, debugging, and result verification; Ding Hao and Tang Chuanxiang were responsible for guidance of the overall experimental scheme and guidance in paper writing. All authors reviewed and approved the publication of the final manuscript.

References

[1] Liu T, Huang N, Yang H, et al. Status and future of the soft X-ray free-electron laser beamline at the SHINE[J]. Frontiers in Physics, Frontiers, 2023, 11.

[2] Kerby J. The advanced photon source upgrade: A brighter future for X-ray science[J]. Synchrotron Radiation News, Taylor & Francis, 2023, 36(4): 26–27.

[3] Raimondi P, Benabderrahmane C, Berkvens P, et al. The extremely brilliant source storage ring of the european synchrotron radiation facility[J]. Communications Physics, Nature Publishing Group, 2023, 6(1): 82.

[4] Bai Zhenghe, Liu Gangwen, He Tianlong, et al. Preliminary physical design of Hefei Advanced Light Facility storage ring[J]. High Power Laser and Particle Beams, 2022, 34(10): 104003-6.

BAI Zhenghe, LIU Gangwen, HE Tianlong, et al. Preliminary physical design of Hefei Advanced Light Facility storage ring[J]. High Power Laser and Particle Beams, 2022, 34(10): 104003.

[5] Jiao Yi, Bai Zhenghe. Physics design and optimization of fourth-generation synchrotron radiation light sources[J]. High Power Laser and Particle Beams, 2022, 34(10): 104004-10.

JIAO Yi, BAI Zhenghe. Physics design and optimization of fourth-generation synchrotron radiation light sources[J]. High Power Laser and Particle Beams, 2022, 34(10): 104004.

[6] Deng X, Chao A, Feikes J, et al. Experimental demonstration of the mechanism of steady-state microbunching[J]. Nature, Nature Publishing Group, 2021, 590(7847): 576–579.

[7] Kruschinski A, Deng X, Feikes J, et al. Confirming the theoretical foundation of steady-state microbunching[J]. Communications Physics, Nature Publishing Group, 2024, 7(1): 160.

[8] Chubar O, Elleaume P. Accurate and efficient computation of synchrotron radiation in the near field region[C]//1998.

[9] Meng X, Shi X, Wang Y, et al. Mutual optical intensity propagation through non-ideal mirrors[J]. Journal of Synchrotron Radiation, International Union of Crystallography, 2017, 24(5): 954–962.

[10] Wang Y, Meng X, Shi X, et al. A software package named MOI is developed for calculating the mutual optical intensity propagation through beamline[C]//Advances in Computational Methods for X-Ray Optics V. SPIE, 2020, 11493: 33–45.

[11] Sanchez del Rio M, Celestre R, Reyes-Herrera J, et al. A fast and lightweight tool for partially

coherent beamline simulations in fourth-generation storage rings based on coherent mode decomposition[J]. Journal of Synchrotron Radiation, International Union of Crystallography, 2022, 29(6): 1354–1367.

[12] Li R, Chubar O. Memory and CPU efficient coherent mode decomposition of partially coherent synchrotron radiation with subtraction of common quadratic phase terms[J]. Optics Express, OSA, 2022, 30: 5896.

[13] Zhou L, Xu H, Li M, et al. The development of coherent modes decoupling method for partially coherent light transport system[J]. Optica Open, 2025.

[14] Nash B, Goldring N, Edelen J, et al. Propagation of partially coherent radiation using wigner functions[J]. Physical Review Accelerators and Beams, American Physical Society, 2021, 24(1): 010702.

[15] Zhong M-C. Propagation of partially coherent light in optical systems[C]//2017.

[16] Leon C, Anisimov P M, Yampolsky N, et al. Using convolutional neural networks to accelerate three-dimensional coherent synchrotron radiation compu-

tations[J]. Physical Review Accelerators and Beams, American Physical Society, 2025, 28(11): 110701.

[17] Grech C, Jafarinia F, Geloni G, et al. Virtual photon pulse characterisation using machine learning methods[J]. .

[18] Sheppard R, Baribeau C, Pedersen T, et al. A neural network model of a quasiperiodic elliptically polarizing undulator in universal mode[J]. Journal of Synchrotron Radiation, International Union of Crystallography, 2022, 29(6): 1368–1375.

[19] Edelen A, Huang X. Machine learning for design and control of particle accelerators: A look backward and forward[J]. Annual Review of Nuclear and Particle Science, Annual Reviews, 2024, 74(Volume 74, 2024): 557–581.

[20] Queipo N V, Haftka R T, Shyy W, et al. Surrogate-based analysis and optimization[J]. Progress in Aerospace Sciences, 2005, 41(1): 1–28.

[21] Lee J M. Riemannian manifolds: an introduction to curvature[M]. 2nd ed. New York Berlin Heidelberg: Springer, 1997.

[22] Hiai F, Petz D. Riemannian metrics on positive definite matrices related to means[J]. arXiv, 2008.

[23] Absil P-A. Optimization Algorithms on Matrix Manifolds[M]. Princeton: Princeton University Press, 2008.

[24] Myers R H. Response Surface Methodology[J]. .

[25] Forrester A I J, Sóbester A, Keane A J. Engineering Design via Surrogate Modelling[J]. .

[26] Duan J, Hesthaven J S. Non-intrusive data-driven reduced-order modeling for time-dependent parametrized problems[J]. Journal of Computational Physics, 2024, 497: 112621.

[27] Halder R, Fidkowski K J, Maki K J. Non-intrusive reduced-order modeling using convolutional autoencoders[J]. International Journal for Numerical Methods in Engineering, 2022, 123(21): 5369–5390.

[28] Snapshot-Based Methods and Algorithms[M]. De Gruyter, 2021.

[29] Box G E P, Wilson K B. On the Experimental Attainment of Optimum Conditions[J]. Journal of the Royal Statistical Society Series B: Statistical Methodology, 1951, 13(1): 1–38.

[30] Cox D R. Response Surfaces, Mixtures, and Ridge Analyses, 2nd Edition by George E.P. Box, Norman R. Draper[J]. International Statistical Review, 2007, 75(2): 265–266.

Note: Figure translations are in progress. See original paper for figures.