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A Data-Driven Approach to Time-Domain Electromagnetic Modeling Based on Dynamic Mode Decomposition

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***Abstract*—This paper presents a data-driven methodology that utilizes Dynamic Mode Decomposition (DMD) for the time-domain (TD) electromagnetic (EM) modeling of microwave devices. As an unsupervised machine learning technique, DMD leverages a limited set of unlabeled spatio-temporal electromagnetic (EM) data to determine DMD eigenvalues and eigenmodes. Then, the obtained DMD model reconstructs the dynamics as a series of exponential terms based on linear assumptions. The effectiveness of this approach is demonstrated through the TD EM modeling of photonic crystal waveguides. Comparative analysis with the finite-difference time-domain (FDTD) method shows that the DMD model not only achieves precise modeling but also facilitates robust short-term forecasting.**

***Index Terms*—Time-domain electromagnetic modeling, finite-difference time-domain method, data-driven approach, dynamic mode decomposition**

I. Introduction

Time-domain (TD) electromagnetic (EM) modeling has been a cornerstone in the field of microwave and photonic devices [1]. Herein, The finite-difference time-domain method (FDTD), pioneered by Yee in 1966 [2], has been particularly influential, providing a versatile and powerful computational technique that has been extensively used in the modeling of electromagnetic wave interactions [3], [4]. This method offers high accuracy and flexibility in handling complex boundaries and media [5]. However, one of the main drawbacks of traditional TD EM modeling approaches, including FDTD, is their computational intensity, which often results in long simulation times [6].

The advent of machine learning (ML) has introduced significant innovations in computational methodologies, revolutionizing various scientific fields, including electromagnetic modeling [7], [8]. ML techniques, such as convolutional neural networks (CNN) and artificial neural networks (ANN), have been employed to enhance or even bypass traditional computational approaches [7]. These methods capitalize on the ability of ML models to learn from large datasets and make predictions. Nevertheless, these supervised ML approaches require extensive labeled datasets for training, which not only demands substantial data collection and labeling efforts but also significant computational resources [9]. In response to these challenges, there is a growing interest in unsupervised machine learning techniques that do not rely on labeled data, offering a promising avenue for efficient and scalable modeling. Unsupervised learning can exploit the inherent structures and patterns in data, providing insights without the need for labeling.

In this study, we leverage dynamic mode decomposition (DMD) to develop a data-driven approach for TD EM modeling. By applying DMD to a set of unlabeled electromagnetic field data collected from simulations of microwave devices, we extract meaningful dynamic modes that significantly simplify the complexity of the system while preserving essential dynamic behaviors. The proposed method not only reduces the computational burden but also provides an effective tool for short-term forecasting and dynamic analysis. We demonstrate the validity and effectiveness of our DMD-based model through comparisons with the FDTD method, showing that DMD not only captures the essential dynamics with fewer computational resources but also provides insights that are not readily accessible through traditional methods.

II. Methodology

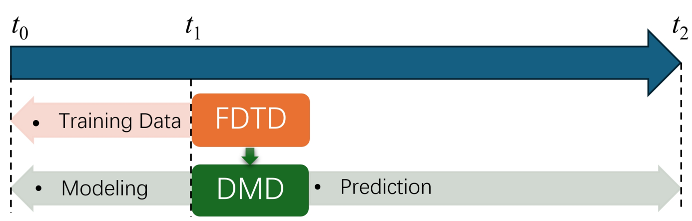

Fig. 1. Schematic of the proposed dynamic mode decomposition-based time-domain electromagnetic modeling method, where the training data is provided by the FDTD method.

Fig. 1 illustrates the proposed DMD-based TD EM modeling method. In the initial phase, spanning from t_0 to t_1, the FDTD method is utilized to generate the requisite training data. Subsequently, this data serves as the basis for the DMD to conduct data-driven modeling. Leveraging the developed DMD model, predictions state of the electromagnetic fields are extrapolated, extending beyond t_1 towards t_2. DMD, originally developed in the field of hydrodynamics and based on Koopman theory [10], is adept at handling complex dynamical systems by decomposing spatiotemporal data into dynamic modes without needing explicit governing equations [11]–[14]. Mathematically, Given the sequence of EM field data $\boldsymbol{e}(t)$ simulated by FDTD from t_0 to t_1 at discrete time intervals, DMD simplifies the representation of the system dynamics through the matrix relation $\boldsymbol{E^2} \approx \boldsymbol{A}\boldsymbol{E}^1$, where $\boldsymbol{E}^1 = [\boldsymbol{e}_0, \boldsymbol{e}_1, \cdots, \boldsymbol{e}_{n-1}]$ and $\boldsymbol{E}^2 = [\boldsymbol{e}_1, \boldsymbol{e}_2, \cdots, \boldsymbol{e}_n]$. $\boldsymbol{A}$ encapsulates the linear dynamics estimated by DMD, which is derived using the singular value decomposition (SVD) of $\boldsymbol{E}^1$, namely $\boldsymbol{E}^1 = \boldsymbol{U\Sigma V}^*$. Then, the matrix $\boldsymbol{A}$ can be obtained by the pseudoinverse of $\boldsymbol{E}^1$ in term of the SVD approximation as: $\boldsymbol{A} = \boldsymbol{E}^2\boldsymbol{V}\boldsymbol{\Sigma}^{-1}\boldsymbol{U}^*$. This is followed by the projection of $\boldsymbol{A}$ onto a lower-dimensional space using the proper orthogonal decomposition (POD) modes contained in $\boldsymbol{U}$, resulting in the compressed form $\widetilde{\boldsymbol{A}}$. The eigendecomposition of $\widetilde{\boldsymbol{A}}$ then reveals the EM system's dynamic modes and their associated temporal behaviors, effectively capturing the underlying dynamics of the em fields. Finally, the modeled EM field solution can be represented by [15]

$$\boldsymbol{e}(t) = \sum_{i=1}^{I} \boldsymbol{\psi}_i b_i \exp(\omega_i t) = \boldsymbol{\Psi b} \exp(\boldsymbol{\Omega} t) \tag{1}$$

This DMD model represents the electromagnetic field solution, which comprises various modes indexed by i (totaling I modes). Each mode's initial amplitude is denoted by b_i. The diagonal matrix $\boldsymbol{\Omega}$ contains ω_i as its diagonal elements, defining the DMD spectrum. $\boldsymbol{\Psi}$ is a matrix with columns representing DMD eigenvectors $\boldsymbol{\psi}_i$, matching the spatial size of the original data snapshot. According to (1), we can make predictions for future time steps, namely beyond from t_1 towards t_2. It is clear that each mode, $\boldsymbol{\psi}_i$, varies over time with a fixed damping factor and frequency from ω_i. Hence, DMD offers a fully data-driven modeling approach without the need for explicit equations.

III. Benchmarks

To validate the proposed method, we consider an example of a ring resonator structure within a 3.05μm $\times$ 3.6μm domain. As shown in Fig. 2, the structure includes a 0.45μm thick horizontal straight waveguide located 0.3μm from the top and a 0.45μm thick ridged circular waveguide with a central radius of 1μm, positioned 0.1μm below the straight waveguide. Both waveguides are composed of material with a relative permittivity of 6, while the surrounding medium is free space with a relative permittivity of 1. 171THz sinusoidal source is employed to excite this ring resonator at the left end of the straight waveguide as a line source along its width. A perfectly matched layer boundary condition is employed in the FDTD simulation, and the E_z wave's propagation through the waveguides is observed as training data for the DMD method.

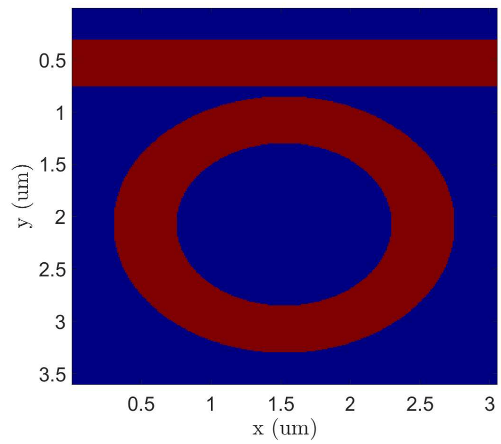

Fig. 2. Schematic of the ring resonator structure

Fig. 3 presents the reconstruction and prediction results utilizing the proposed MD method. Specifically, data spanning from time indices 0 to 1000 served as the training set for DMD to reconstruct the E_z field distributions. Fig. 3(a) illustrates the original E_z field distribution at time index 500, as simulated by the FDTD method. Fig. 3(b) displays the corresponding DMD-based reconstruction at the same time index, demonstrating a close approximation to the FDTD simulation. This level of accuracy is also evident in the comparison between Fig. 3(c) and (d) at time index 800. Employing the DMD model, as outlined in (1), predictions for the E_z field distribution can be obtained. Fig. 3(f) depicts the predicted E_z field at time index 1500. For comparative analysis, Fig. 3(e) provides the corresponding FDTD simulation results at the same future time index. The notable agreement between the predicted values (Fig. 3(f)) and the actual FDTD simulation results (Fig. 3(e)) clearly demonstrates the effectiveness and precision of the DMD model in forecasting the dynamics of EM fields over time. The peak signal-to-noise ratio (PSNR) is used to measure these reconstruction and prediction results, as shown in Table I. Hence, we can conclude that as an unsupervised learning method, DMD can use a small amount of unlabeled data to model the EM system, and the model has good reconstruction and prediction capabilities.

IV. Conclusion

In summary, we presented a data-driven methodology using DMD for TD EM modeling of a ring resonator. DMD, as an unsupervised ML technique, provides a data-driven approach for capturing dynamic behaviors in EM systems without the need for equations. The effectiveness of the DMD-based model is demonstrated through comparisons with the FDTD simulation. This approach offers a promising data-driven avenue for efficient TD EM modeling.

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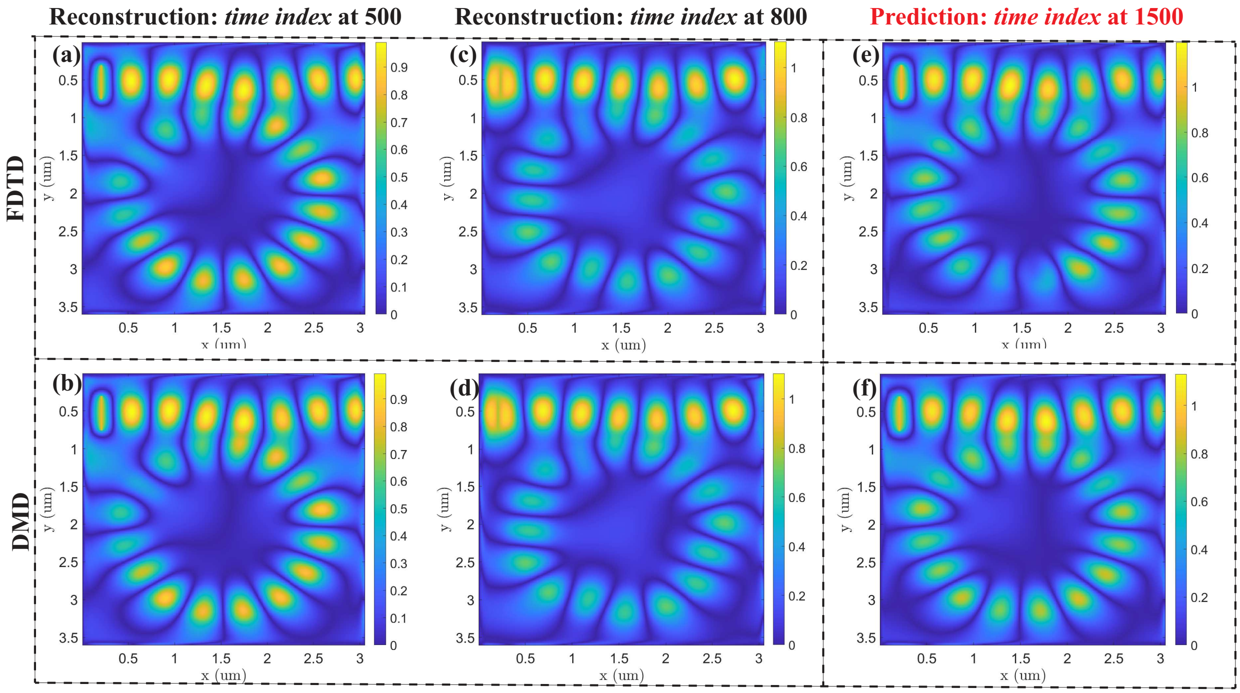

Fig. 3. Reconstruction and prediction of E_z field distributions using the proposed DMD method: (a) the original field at time index 500 simulated by FDTD and (b) the corresponding reconstruction obtained by DMD; (c) the original field at time index 800 simulated by FDTD and (d) the corresponding reconstruction; (f) the prediction result at time index 1500 provided by DMD and (e) the corresponding comparison obtained by the FDTD.

TABLE I
COMPARISON OF PEAK SIGNAL-TO-NOISE RATIO OF THE RECONSTRUCTION AND PREDICTION RESULTS SHOWN IN FIG. 3

	Time Index	PSNR
Reconstruction	500	41.9455 dB
	800	41.2705 dB
Prediction	1500	23.1686 dB

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