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Physics-Informed Machine Learning for UAV Control

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***Abstract*—The integration of Dynamic Mode Decomposition (DMD) control with Physics-Informed Neural Networks (PINNs) offers a novel approach to enhancing UAV quadcopter control systems. This method leverages DMD techniques and PINNs to solve the Riccati equation, which is essential for precise UAV position estimation. By framing the UAV control problem within physics-based constraints, the approach ensures that the learned models adhere to the physical laws governing UAV dynamics. Utilizing a comprehensive dataset—including UAV flight parameters such as position, velocity, and control inputs—DMD extracts fundamental dynamic modes from the data, providing a reduced-order representation that captures the dominant UAV dynamics. This reduced representation is then incorporated into the PINN framework to accurately solve the Riccati equation. The combination of DMD and PINNs results in a robust control strategy that significantly improves position estimation accuracy and optimizes control performance. Real-time validation of this method was conducted in a Unity-based physics simulation environment, incorporating factors like gravity and perturbation noise. The results demonstrate substantial improvements in estimation accuracy and control stability compared to traditional methods.**

***Index Terms*—Dynamic Mode Decomposition (DMD), Physics-Informed Neural Networks (PINNs), Unmanned Autonomous Vehicle (UAV), Riccati equation, Deep Learning, drone trajectory.**

I. Introduction

Unmanned Aerial Vehicles (UAVs) are increasingly vital in diverse applications such as surveillance [1], mapping [2], warehouse inspection [3], delivery services [4], and environmental monitoring [5]. Achieving precise control and accurate position estimation is crucial for effectively deploying UAVs, particularly in highly complex and rapidly evolving environments. State-of-the-art control strategies have been developed to address these challenges, including Proportional-Integral-Derivative (PID) control [6], Model Predictive Control (MPC) [7], Deep Learning control [8], [9], genetic algorithms [10] and Linear Quadratic Regulators (LQR) [11]. While these methods have shown success in specific scenarios, they often struggle with real-time adaptability and robustness in the presence of perturbations and noise.

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Dynamic Mode Decomposition (DMD) [12] has emerged as a powerful technique for capturing the essential dynamics of complex systems through data-driven approaches. However, DMD alone is insufficient to provide sufficient robustness in highly dynamic and noisy environments, as it primarily focuses on identifying dominant modes without explicitly incorporating the underlying physical laws. This limitation can lead to reduced UAV position estimation and control accuracy, particularly in environmental perturbations such as wind or other noise conditions. To overcome these limitations, this paper introduces a novel approach that integrates DMD control with Physics-Informed Neural Networks (PINNs) to enhance UAV control systems [13]. The proposed method leverages DMD techniques to extract critical dynamic modes from a comprehensive dataset that includes UAV flight information such as position, velocity, and control inputs. These modes provide a reduced-order representation that captures the dominant UAV dynamics. This representation is then used within the PINN framework to solve the Riccati equation [14], [15] with high accuracy, ensuring that the learned models conform to the physical laws governing UAV dynamics [16].

Combining DMD and PINNs creates a robust control strategy that provides accurate position estimations and enhances control performance. This approach is efficient in environments with perturbations and noise, ensuring reliable UAV operation under challenging conditions [17]. Experimental results validate the efficacy of the proposed method for real-time UAV control in a simulated Unity environment. The method demonstrates significant improvements in estimation accuracy and control stability compared to traditional approaches.

This work marks a pivotal advancement in developing intelligent, data-driven UAV control systems for a quadcopter, opening new avenues for research in autonomous flight control. By integrating DMD and PINNs, we aim to develop robust path trajectory solutions that can withstand environmental perturbations, providing a reliable and adaptable control framework for UAVs. Therefore, in this work, we propose the following:

- We proposed a DMD-PINN model for estimation the position drone trajectory.
- Present a proposal to simulate drone trajectories for

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training UAVs within a Unity environment, accounting for various conditions that may affect the drone's path.

II. DYNAMIC MODE DECOMPOSITION (DMD) CONTROL FOR UAV

Dynamic Mode Decomposition (DMD) is a data-driven technique used to decompose complex dynamical systems into a set of dynamic modes, enabling a reduced-order representation that captures the essential behavior of the system (see Fig. 1). DMD has gained traction in UAV control due to its ability to identify and isolate dominant patterns from high-dimensional data, making it suitable for real-time control applications [12].

A. State-Space Representation

For UAVs, the equations of state typically describe the evolution of the system's position and orientation over time [18]. The state vector x_k can include position coordinates (x, y, z) and Eular angles (ϕ, θ, ψ), representing roll, pitch and yaw respectively. The continuos-time state-space model is given by Eq.(1) [14].

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + w_k \\ y_k &= Cx_k + v_k \end{aligned} \tag{1}$$

where x_k is the state vector at time step k, including position (x, y, z) and orientation (roll, pitch, yaw), A is the system matrix, B is the input matrix, u_k is the control input vector, w_k is the process noise vector and v_k measurement noise. DMD is used to approximate the system dynamics by identifying the matrix A and B from the collected flight data. The procedure involves collecting snapshots of the state vector over time and using these to compute the DMD modes. To control the UAV, we solve the discrete algebraic Riccati equation (DARE) [19] to obtain the optimal state feedback gains.

B. Solving the Riccati Equation

To achieve accurate position estimation, the discrete algebraic Riccati equation (DARE) is solved. The DARE is given by Eq.(2):

$$X = A^T XA - A^T XB \left(R + B^T XB\right)^{-1} B^T XA + Q, \tag{2}$$

where X is the solution to the Riccati equation (2), Q and R are weighting matrices that penalize the state and control input, respectively. The control law derived from solving the Riccati equation Eq.(3):

$$u_k = -\left(R + B^T XB\right)^{-1} B^T XAx_k, \tag{3}$$

C. Limitations in the Presence of Noise

One of the significant challenges in using DMD control for UAVs is its sensitivity to noise. Process noise $w_k(t)$ and measurement noise v_k can introduce inaccuracies in the estimation of the system matrices A and B. This, in turn, affects the accuracy of the reduced-order model and the solution to the Riccati equation.

In the presence of noise, the estimated state $\hat{x}_k$ may deviate from the true state x_k, leading to suboptimal control inputs. The effect of noise can be mitigated to some extent by incorporating robust filtering techniques, such as the Kalman filter [20], which can help improve state estimation by accounting for noise in the measurements.

However, despite these techniques, noise remains a significant limitation in achieving precise control. The integration of PINNs with DMD aims to address this limitation by incorporating physical constraints directly into the learning process, ensuring that the model adheres to the underlying physics of UAV dynamics even in noisy environments. This integration enhances the robustness and accuracy of UAV control, making it more reliable under various perturbations.

III. DYNAMIC MODE DECOMPOSITION (DMD) WITH PHYSICS-INFORMED NEURONAL NETWORK (PINNS)

Integrating DMD and PINNs offers a robust control strategy that accurately estimates the UAV's position and orientation, even in noise and environmental perturbations. By minimizing the composite loss function, the PINN framework ensures that the estimated states conform to the physical laws of UAV dynamics, resulting in improved accuracy and stability. The training process involves adjusting the neural network parameters to minimize these loss functions, thereby enhancing the overall performance of the control system (see Fig. 2).

For the process of integration DMD with PINN define the following steps:

1) **Data Acquisition and Preprocessing:** A comprehensive dataset comprising UAV flight information X_{in}, including Euler angles (ϕ, θ, ψ), position coordinates (x, y, z), and noisy observations . This dataset serves as the input for the DMD process.
2) **Dynamic Mode Decomposition (DMD):** The input data is processed using DMD to extract the system matrices $\begin{bmatrix} A & B & Q & R \end{bmatrix}$ representing the UAV dynamics and control parameters. These matrices create a reduced-order model that captures the dominant modes of the UAV's behavior.
3) **Solving the Discrete Algebraic Riccati Equation (DARE):** The matrices obtained from DMD are used to solve the discrete algebraic Riccati equation (DARE), providing an initial state estimate $\hat{X}_1$. The Riccati equation is given by Eq. (2)
4) **Neural Network (NN) Refinement:** The initial state estimate $\hat{X}_1$ is then refined using a Physics-Informed Neural Network (PINN). The architecture consists of fully connected layers with ReLU activation functions between layers:
   - **Input Layer:** The network takes as input system matrices.
   - **First Layer:** The flattened input passes through a fully connected layer with 128 neurons, followed by a ReLU activation.

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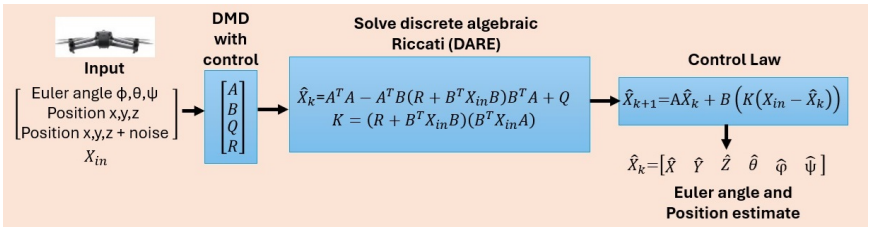

Fig. 1: Process of integrating Dynamic Mode Decomposition (DMD) with control to solve the discrete algebraic Riccati equation (DARE) for UAV position and orientation estimation.

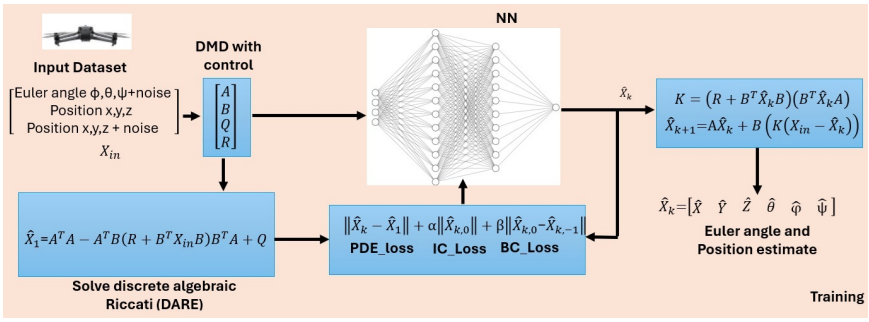

Fig. 2: Process of integrating DMD with PINN for UAV position and orientation estimation. The sequence illustrates the training process, including the loss function and neural network architecture.

- **Second Layer:** The output of the first hidden layer is passed through another fully connected layer with 128 neurons, again followed by a ReLU activation.
- **Output Layer:** The output from the second hidden layer is passed through a final fully connected layer that outputs a vector reshaped into the desired size of A (state dimension squared), producing an estimated matrix $\hat{X}_k$ for the given system. This matrix represents a control output in the form of a transformation of the input matrices.

This neural network framework incorporates physical laws and constraints directly into the learning process, improving the accuracy of the state estimates. The refinement process involves minimizing a composite loss function, where the variable α=0.1 and β=0.05 used to adjust the loss function:

$$L = \left\|\hat{X}_k - \hat{X}_1\right\| + \alpha \left\|\hat{X}_{k,0}\right\| + \beta \left\|\hat{X}_{k,0} - \hat{X}_{k,-1}\right\|, \quad (4)$$

- **PDE Loss** $\left\|\hat{X}_k - \hat{X}_1\right\|$**:** Ensures that the neural network solution adheres to the partial differential equations governing the UAV dynamics.
- **Initial Condition Loss** $\alpha \left\|\hat{X}_{k,0}\right\|$**:** Penalizes deviations from the initial conditions.
- **Boundary Condition Loss** $\beta \left\|\hat{X}_{k,0} - \hat{X}_{k,-1}\right\|$**:** Ensures continuity and smoothness in the state estimates over time.

5) **Control Law and Position Estimate:** The refined state estimate $\hat{X}_k$ is used to update the control law. The control law is given by:

$$\begin{aligned} \hat{X}_k &= A^T A - A^T B \left(R + B^T \hat{X}_{in} B\right)^{-1} B^T A + Q \\ K &= \left(R + B^T \hat{X}_{in} B\right)^{-1} \left(B^T \hat{X}_{in} A\right) \end{aligned} \quad (5)$$

This step involves computing the optimal control inputs based on the refined state estimates to achieve accurate UAV position and orientation control.

6) **Output:** The final output $\hat{X}_k$ consists of the estimated position $(\hat{x}, \hat{y}, \hat{z})$ and Euler angles $\left(\hat{\phi}, \hat{\theta}, \hat{\psi}\right)$.

A. Training

The training process for the PINNs involves adjusting the neural network parameters to minimize the composite loss functions Eq. (4). By incorporating physical constraints and leveraging the DMD-extracted dynamic modes, the PINNs framework ensures robust and accurate UAV state estimations, even in noise and environmental perturbations. For training, we used the IMCIS [21] and Package Delivery UAV [22] datasets. The network was trained for a maximum of 5000 iterations, with an early stopping criterion based on a network error tolerance of 10^{-4}. The Adam optimizer was utilized, and the training duration ranged from 30 to 50 minutes. The network configuration included three fully connected (Linear) layers and two ReLU activation functions. The calculations were executed using an NVIDIA GTX GeForce RTX 4060 graphics processing unit (GPU). For testing the model (for example, we considered four different trajectory cases as shown in Figure 3), we developed an environment in Unity that includes a physics-based simulation incorporating factors such

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TABLE I: Comparison of UAV control performance metrics for DMD,DMD-PINN,Multiple Linear Regressor (MLP),CNN approaches. The metrics include RMSE, MAE, and R^2. The DMD-PINN approach shows improved performance with lower RMSE and MAE values and a higher R^2 value compared to the DMD approach.

Method	RMSE	MAE	R^2
MLR [25]	143.47	75.37	0.49
CNN [26]	89.63	37.31	0.42
DMD	20.58	16.55	0.58
PINN	8.92	7.35	0.37

as gravity and perturbation noise. The integration between the control model and the simulation environment was achieved using the UDP communication protocol (see Fig. 4).

IV. SIMULATION RESULTS

To evaluate the proposed neural network model, we trained it using the IMCIS and Package Delivery UAV datasets, specifically designed for a quadcopter UAV. To simulate real-world outdoor conditions, the data was augmented with noise. The model's performance was tested in a Unity simulation environment (see Fig. 4), using 200 trials. We compared its results against DMD, CNN, and MLR models, as well as the proposed PINNs, by calculating key performance metrics: Root Mean Square Error (RMSE) [23], Mean Absolute Error (MAE) [23], and the coefficient of determination (R^2) [24].

The results indicated that the DMD-PINN model achieved lower RMSE and MAE values and a higher R^2 value, reflecting more accurate and reliable trajectory control (see Table I). The improvements observed when applying PINNs over the simple DMD model are evident in these metrics. The testing results, including position estimates (x, y, z) with added noise for different cases, are presented in Figures 5.

V. DISCUSSION SIMULATION RESULTS

The integration of DMD with PINNs has substantially improved UAV trajectory control, as demonstrated through both quantitative and qualitative metrics. The DMD-PINN model achieved significantly lower RMSE and MAE compared to alternative models, including CNN, MLR, and the DMD-only model (see Table I). These results underscore its superior accuracy and reliability in controlling UAV trajectories. Furthermore, the DMD-PINN model exhibited closer alignment with ground truth trajectories and demonstrated robust performance across various test scenarios, indicating a substantial leap in the model's ability to handle noise and maintain precision in dynamic environments. This blend of DMD with PINNs suggests a robust methodology for improving the fidelity of UAV control systems under diverse operational conditions.

VI. EMBEDDED SYSTEM FEASIBILITY

To deploy the PINN model on embedded systems for drones, we focus on widely-used architectures like the Nvidia Jetson Nano and the Raspberry Pi. The Nvidia Jetson Nano is particularly well-suited for this application due to its GPU acceleration, which makes it highly feasible for real-time tasks. Conversely, while the Raspberry Pi is capable of running the model, it may necessitate performance enhancements such as reduced precision or optimized inference frameworks to meet the stringent real-time control requirements. Although the architecture is manageable on the Jetson Nano, achieving real-time performance on the Raspberry Pi requires further optimizations, particularly for control applications that necessitate immediate feedback and adjustments.

VII. CONCLUSION

The combination of DMD with PINNs has significantly improved UAV trajectory control, as demonstrated by the superior performance indicators of the DMD-PINN model. Achieving significantly lower RMSE and MAE values, and a higher R^2 score than the standalone DMD model, this hybrid approach has proven its ability to provide more precise and reliable trajectory estimations. Through various test cases, the DMD-PINN model demonstrated its robustness in accurately following ground truth trajectories with minimal deviation and noise, especially under challenging conditions. This integration not only improves the accuracy and efficiency of UAV control systems but also establishes a framework to optimize UAV performance across diverse operational scenarios.

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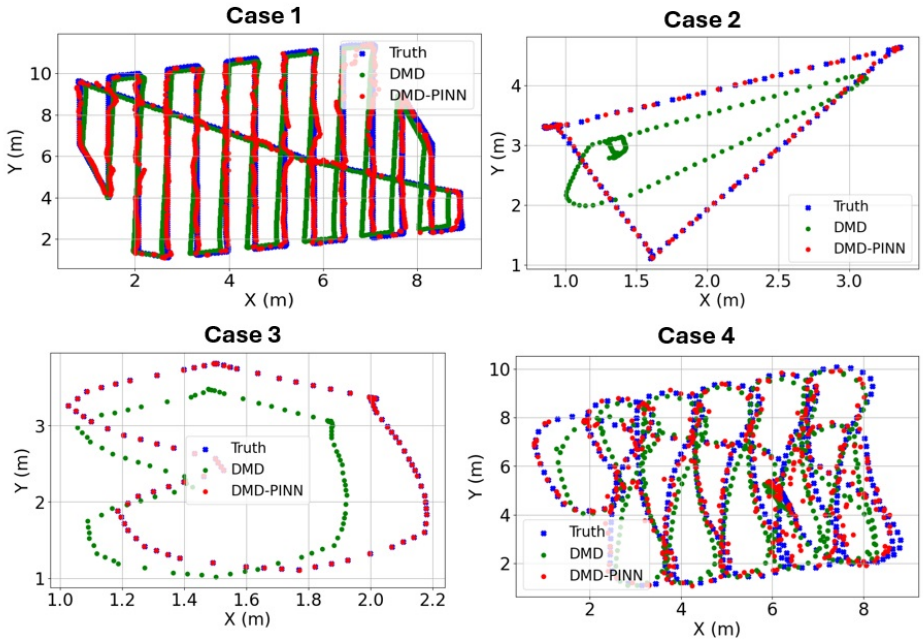

Fig. 3: Reference drone trajectory used for evaluating the performance of DMD and PINN control methods.

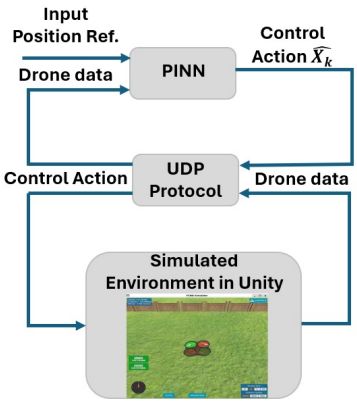

Fig. 4: The proposed framework design outlines the interaction between the PINN control system and the Unity environment, facilitated through the UDP communication protocol.

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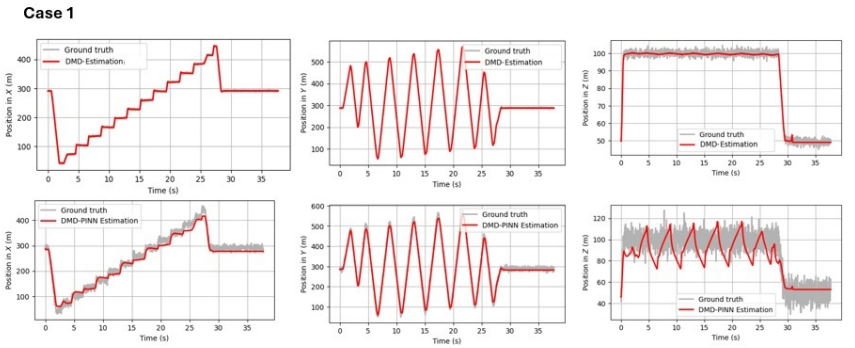

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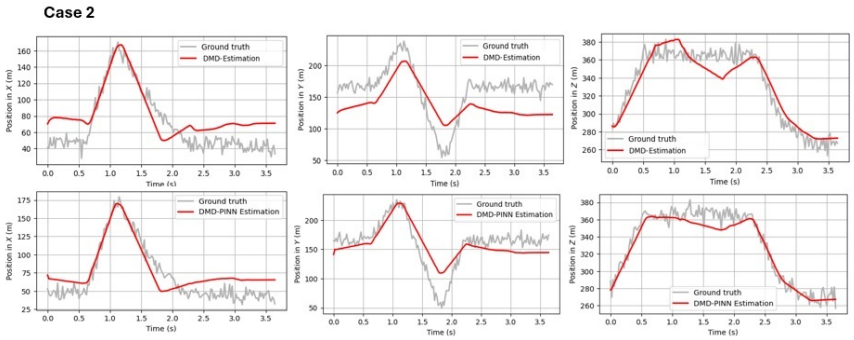

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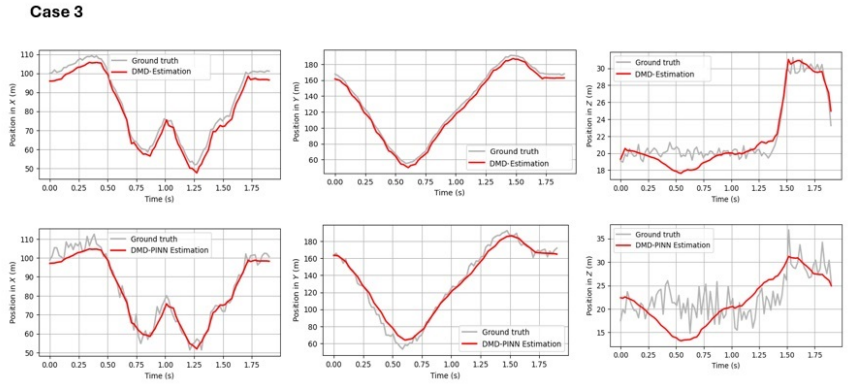

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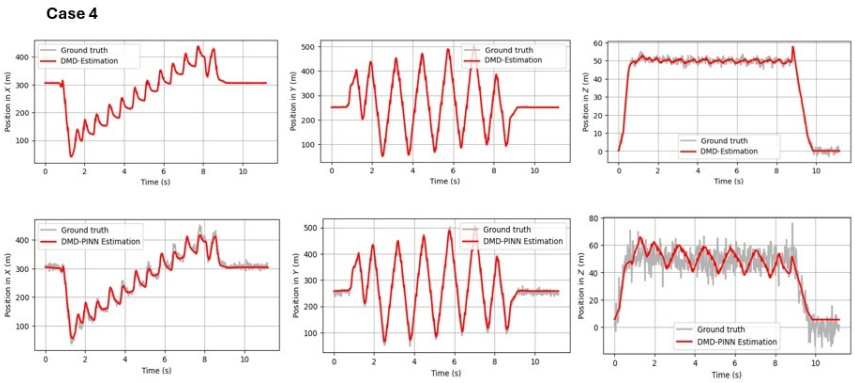

(d)

Fig. 5: Trajectory estimation results from test cases comparing DMD-LQR and DMD-PINN approaches are presented for the ground truth versus estimated trajectories in the x, y, and z coordinates. The cases are as follows: (a) Case 1: Trajectory in Fig. 3a, (b) Case 2: Trajectory in Fig. 3b, (c) Case 3: Trajectory in Fig. 3c, and (d) Case 4: Trajectory in Fig. 3d.

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