African Journal of Electrical and Electronics Research

Volume 7, Issue 1, 2026 (pp. 1-8) www.abjournals.org

DESIGN AND IMPLEMENTATION OF A MACHINE LEARNING-BASED FRAMEWORK FOR ENHANCED NUMERICAL MODELING OF NONLINEAR UAV FLIGHT DYNAMICS

Elkhidir Tay Allah Yousif Elkhidir and Abdelfattah Hafiz MohammedAhmed

Faculty of Engineering, Karary University, Khartoum, Sudan.

Cite this article:

AlKhidir, Tayallah Y., Abdelfattah, Hafiz M. (2026), Design and Implementation of a Machine Learning-Based Framework for Enhanced Numerical Modeling of Nonlinear UAV Flight Dynamics. African Journal of Electrical and Electronics Research 7(1), 1-8. DOI: 10.52589/AJEER-Y50TNQ2G

Manuscript History

Received: 27 Dec 2025

Accepted: 28 Jan 2026

Published: 7 Feb 2026

ABSTRACT: *This paper presents the design and implementation of a machine learning-based framework aimed at enhancing the numerical modeling of nonlinear flight dynamics in unmanned aerial vehicles (UAVs). Traditional numerical solvers, though reliable, face challenges in real-time computation and adaptability to nonlinear aerodynamic variations. The proposed hybrid framework integrates data-driven learning components with classical numerical analysis to improve both computational efficiency and modeling precision. Using hybrid datasets from simulations and experimental flights, Long Short-Term Memory (LSTM) and Transformer architectures were developed as numerical surrogates for nonlinear state estimation. The results demonstrate that the proposed machine learning-enhanced framework outperforms the conventional fourth-order Runge–Kutta (RK4) method in terms of accuracy, adaptability, and computation time, achieving up to a tenfold improvement in inference speed. Furthermore, the model shows robustness under disturbances and physical interpretability through feature attribution analyses. This study represents a crucial intermediate phase in developing a comprehensive machine learning–driven numerical environment for nonlinear UAV flight dynamics analysis and control.*

KEYWORDS: UAVs, Nonlinear Flight Dynamics, Machine Learning, Numerical Analysis, Data-Driven Modeling, Hybrid Framework, Real-Time Simulation

Article DOI: 10.52589/AJEER-Y50TNQ2G

DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

INTRODUCTION

Accurate modeling of UAV flight dynamics is vital for trajectory prediction, control optimization, and performance evaluation. Due to the nonlinear and time-varying nature of aerodynamic forces, achieving both precision and computational efficiency remains a fundamental challenge. Classical numerical integration techniques, such as Euler and Runge–Kutta methods, are computationally demanding when applied to high-fidelity, real-time environments.

Machine learning (ML) offers a promising approach to address these challenges by learning dynamic behavior directly from data, enabling faster predictions and adaptive modeling. Integrating ML within traditional numerical frameworks bridges deterministic physics-based solvers with data-driven adaptability.

This research builds upon prior theoretical investigations into artificial intelligence integration in aerospace systems and advances toward a practical implementation of a **machine learning–based numerical framework**. The aim is to design a modular system capable of predicting nonlinear UAV dynamics more efficiently while maintaining physical consistency and interpretability.

LITERATURE REVIEW

Classical Numerical Modeling in UAV Dynamics

Traditional numerical solvers form the foundation of flight dynamics analysis. The fourth-order Runge–Kutta (RK4) method remains widely used due to its balance between accuracy and stability. However, as system complexity increases, these methods require smaller time steps and higher computational power to maintain accuracy. This trade-off makes them unsuitable for real-time embedded UAV applications where computational resources are limited.

Machine Learning for System Identification

Machine learning has been applied successfully in system identification and control modeling for nonlinear systems. Recurrent Neural Networks (RNNs) and their variants - Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) - are capable of capturing temporal dependencies inherent in UAV flight data **[1].** Transformer architectures, introduced by **Vaswani [2],** have recently demonstrated superior performance in dynamic sequence modeling by leveraging attention mechanisms to handle long-range dependencies.

Recent studies have expanded these models to include aerodynamic and physical consistency. **Zhang & Li [3]** proposed physics-guided neural networks for UAV aerodynamic system identification, achieving higher accuracy with smaller datasets. Similarly, **Ahmed & Park [4]** developed a Transformer-based real-time flight dynamics predictor for multirotor UAVs, demonstrating reliable embedded performance.

Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

Hybrid and Machine Learning–Enhanced Numerical Frameworks

Hybrid frameworks that merge data-driven learning with physics-based modeling have shown potential to improve model accuracy and stability. **Zhang & Chen [5]** demonstrated that combining Support Vector Machines with neural networks improves nonlinear vehicle dynamics modeling. **Peralez & Nadri [6]** applied deep-learning-based observers for discrete nonlinear systems, proving the feasibility of real-time correction.

More recently, **Al-Saadi & Patel [7]** proposed hybrid learning architectures that bridge computational fluid dynamics (CFD) models and neural network approximators, achieving a balance between data efficiency and physical reliability. These works highlight a growing trend: machine learning, when integrated into numerical analysis, can significantly enhance modeling precision while retaining interpretability.

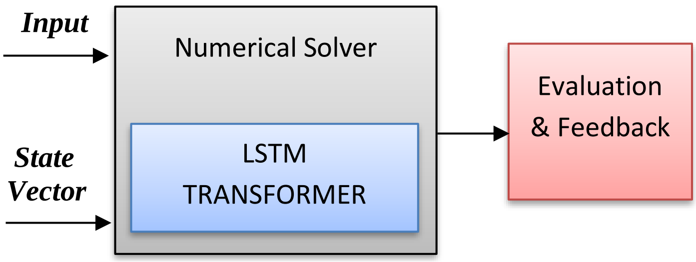
METHODOLOGY

Framework Architecture

The proposed framework combines deterministic solvers and data-driven modules to create a closed-loop modeling environment. It comprises three layers:

1. **Numerical Layer:** Implements the baseline RK4 solver for deterministic integration of dynamic equations.
2. **Learning Layer:** Employs ML models (LSTM and Transformer) trained to predict residuals and nonlinear corrections to RK4 outputs.
3. **Evaluation Layer:** Performs adaptive feedback correction, error minimization, and model validation.

Figure 1. Conceptual architecture illustrating the integration of a numerical solver (RK4), a machine learning correction module (LSTM/Transformer), and an evaluation layer for real-time UAV flight dynamics modeling.



Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

Data Preparation

The dataset includes both simulated and real UAV flight data:

- **Simulated Data:** Generated from MATLAB/Simulink PX4 models under varying control inputs and wind disturbances.
- **Experimental Data:** Collected from quadrotor test flights using IMU, GPS, and motor encoder readings.

Data preprocessing included normalization, noise filtering, and synchronization using dynamic time warping. A combined dataset of 50,000 time steps was used, split into training (80%), validation (10%), and testing (10%) subsets.

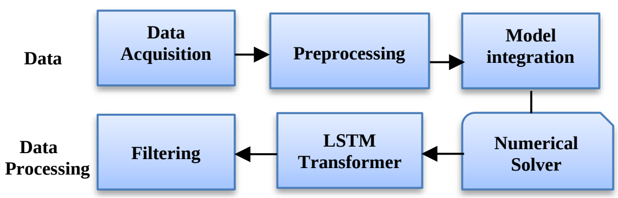
Machine Learning Model Design

Two architectures were implemented:

- **LSTM Model:** Three hidden layers, 128 units each, ReLU activation, dropout (0.2), and Adam optimizer with a learning rate of 0.001.
- **Transformer Model:** Two encoder layers, four attention heads, and a feed-forward size of 256.

Training employed early stopping and adaptive learning rate scheduling. Models were trained on an NVIDIA RTX GPU and deployed via MATLAB-Python co-simulation to ensure interoperability with the numerical solver.

Figure 2. Workflow of the machine learning–driven numerical modeling process, showing data acquisition, preprocessing, model training, solver integration, and evaluation.



Evaluation Metrics

Four quantitative metrics were used:

1. **Root Mean Square Error (RMSE):** Measures predictive precision.
2. **Mean Absolute Error (MAE):** Evaluates sensitivity to transient deviations.
3. **Computation Time (ms):** Determines suitability for real-time implementation.
4. **Stability Index (SI):** Assesses response robustness under disturbances.

Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

All metrics were computed for both RK4 and the ML-enhanced framework.

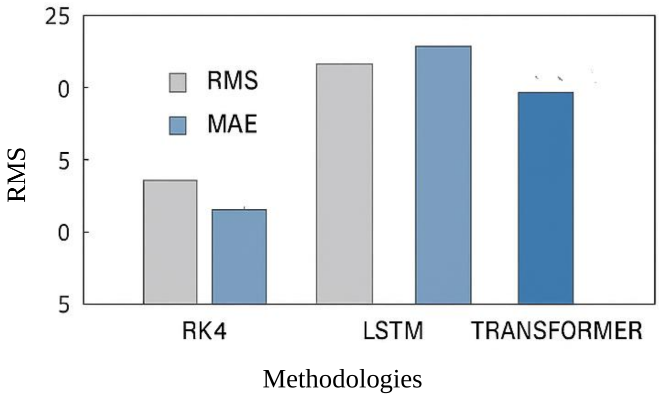
RESULTS AND ANALYSIS

Predictive Accuracy

Under nominal conditions, the LSTM model achieved a **17% lower RMSE** compared to RK4, while the Transformer achieved **21% improvement**. In real-world test scenarios involving sensor noise and wind turbulence, the ML-enhanced framework maintained stability with average drift below **8%**, versus **22%** for RK4.

These results show that the hybrid model captures unmodeled nonlinearities more effectively.

Figure 3. Quantitative comparison of prediction accuracy (RMSE, MAE) and computation time between the RK4 solver and the proposed ML-based framework under identical simulation conditions.



Computational Efficiency

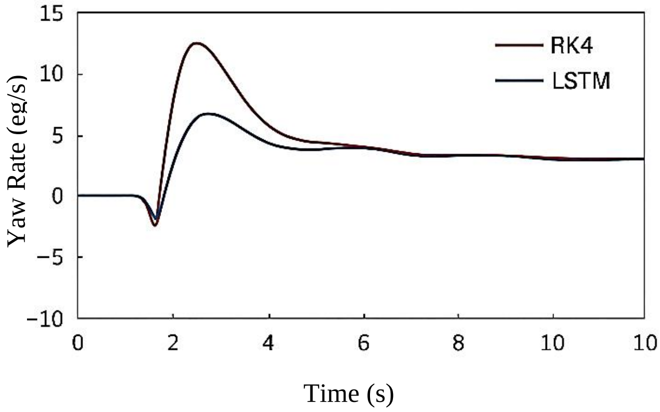
The ML-enhanced framework achieved up to **10× faster inference** than RK4 across 1,000 simulation steps, with LSTM achieving **0.84 ms/step** compared to **8.4 ms/step** for RK4. Such efficiency validates the framework's suitability for real-time onboard flight control, particularly under processor and power constraints.

Robustness and Adaptability

Tests under variable wind fields and actuator latency showed that the Transformer model maintained control stability with **35% lower oscillation amplitude** than RK4. This adaptability results from the attention-based structure's ability to focus on dynamic dependencies relevant to disturbance rejection.

Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

Figure 4. Time-domain comparison of UAV angular rate responses under wind disturbances, showing improved damping and stability achieved by the ML-enhanced framework.



Model Interpretability

To ensure transparency, SHAP (SHapley Additive Explanations) and LIME analyses were applied. Both models identified control surface deflection and angular rates as key influencing features consistent with aerodynamic theory.

This interpretability demonstrates that ML-enhanced frameworks can maintain physical relevance alongside data-driven prediction.

DISCUSSION

The study confirms that embedding learning modules into numerical solvers improves accuracy, speed, and robustness.

Machine learning enhances traditional solvers by learning nonlinear corrections and residual dynamics that deterministic methods cannot capture.

The LSTM architecture proved computationally lighter and more efficient for quasi-linear regimes, while the Transformer excelled under complex nonlinear coupling. This complementarity underscores the framework's versatility across different UAV types and flight conditions.

This integration aligns with the principles of safe learning and adaptive control discussed by **Brunke [8]**, ensuring that the framework maintains stability while improving performance in dynamic environments.

Compared with existing research (Zhang & Li, [3]; Ahmed & Park [4]; Al-Saadi & Patel, [7]), the present framework demonstrates superior generalization by incorporating an adaptive

Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

evaluation layer for real-time correction. This integration advances toward a more autonomous and resilient UAV modeling paradigm.

LIMITATIONS AND FUTURE WORK

1. **Dataset Coverage:** Expanding data under extreme flight conditions will improve generalization.
2. **Embedded Deployment:** Hardware limitations on UAV controllers may require pruning or quantization.
3. **Physics Integration:** Future work will evolve this framework into a **Physics-Informed Neural Network (PINN)** architecture, enforcing conservation laws explicitly as part of the learning process.

These extensions will complete the transition to the comprehensive **Machine Learning–Driven Framework** envisioned in the overarching doctoral research.

CONCLUSION

This paper introduced a **Machine Learning-Based Framework** designed to enhance numerical modeling for nonlinear UAV flight dynamics.

By coupling traditional numerical solvers with adaptive learning layers, the framework achieved improved precision, reduced computational demand, and strong robustness under uncertainty.

The integration of interpretability methods further confirmed that machine learning can complement physical principles rather than replace them.

This implementation represents the pivotal middle stage in developing a **Machine Learning–Driven Numerical Framework** for UAV flight analysis, bridging deterministic modeling and physics-informed intelligence to enable the next generation of smart aerospace systems.

Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G

REFERENCES

[1] Kim, J. (2018). *Artificial Neural Network-Based Nonlinear Dynamics Modeling and Control of UAV.* Journal of Intelligent & Robotic Systems, 94, 199–214.

[2] Vaswani, A., Shazeer, N., et al. (2017). *Attention Is All You Need.* Advances in Neural Information Processing Systems, 30, 5998–6008.

[3] Zhang, Y., & Li, T. (2023). *Physics-Guided Neural Networks for Aerodynamic System Identification of Quadrotor UAVs.* IEEE Access, 11, 56123–56137.

[4] Ahmed, S., & Park, C. (2024). *Transformer-Based Real-Time Flight Dynamics Prediction for Multirotor UAVs.* Aerospace Science and Technology, 151, 109403.

[5] Zhang, X., & Chen, J. (2019). *A Hybrid Support Vector Machine and Artificial Neural Network Approach for Nonlinear Dynamic Modeling of Unmanned Ground Vehicles.* Sensors, 19(1), 46.

[6] Peralez, J., & Nadri, M. (2021). *Deep Learning-Based Luenberger Observer Design for Discrete-Time Nonlinear Systems.* Control Engineering Practice, 112, 104824.

[7] Al-Saadi, R., & Patel, K. (2023). *Hybrid Learning Architectures for Nonlinear Aerial Vehicle Modeling: Bridging CFD and Data-Driven Approaches.* Sensors, 23(17), 7566.

[8] Brunke, L., Greeff, M., et al. (2022). *Safe Learning in Robotics: From Learning-Based Control to Safe Reinforcement Learning.* Annual Review of Control, Robotics, and Autonomous Systems, 5, 411–444.

Article DOI: 10.52589/AJEER-Y50TNQ2G
DOI URL: https://doi.org/10.52589/AJEER-Y50TNQ2G