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A Review on Multistage CFD and AIML Based Hybrid Wind-Hydro Turbine

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Abstract:
Rapid industrialization has propelled economic expansion while simultaneously intensifying global energy consumption, fossil fuel dependence, and ecological degradation. As the world transitions toward sustainable development and net-zero emissions, innovative, robust, and eco-friendly energy systems are urgently required. This study presents a Hybrid Computational Fluid Dynamics–Artificial Intelligence (CFD–AI) framework for advanced turbine design and performance enhancement. The model integrates high-resolution CFD simulations with AI/ML algorithms to optimize multi-stage hybrid turbines, particularly suited for decentralized renewable microgrids in rural and semi-urban areas with variable resource availability. CFD accurately captures intricate flow behaviors and operational characteristics, while AI/ML models dynamically forecast performance, adapting to changing wind, hydro, and environmental inputs. Predictive efficiency is achieved through supervised learning models such as Random Forest and Gradient Boosting (XGBoost/LightGBM), complemented by Feedforward and Physics-Informed Neural Networks (PINNs) for physics integration and computational cost reduction. Long Short-Term Memory (LSTM) networks handle time-series predictions for power output fluctuations. This synergistic approach enables highly flexible and efficient turbine systems. Integrated energy storage units (e.g., battery banks) further stabilize supply and scalability for localized end-users like homes, schools, and industries. The reviewed literature demonstrates that hybrid CFD–AI strategies can boost output stability by up to 20% compared to conventional designs, significantly reducing reliance on fossil fuels. The research aligns with United Nations Sustainable Development Goals on clean energy, sustainable communities, and climate action, illustrating how emerging technologies can transform industrial challenges into pathways toward a greener, equitable, net-zero future.

Index Terms: CFD, AI/ML, Sustainable Development, Net-Zero Energy, Microgrids, Decentralized, Renewable Energy, Hybrid Turbine, Turbine Optimization, Energy Storage, Hybrid Systems, Wind-Hydro Turbine, Gradient Boosting, XGBoost, LightGBM.

I. INTRODUCTION

The global push for sustainable energy demands resilient, low-carbon technologies. Hybrid renewable systems that pair complementary resources such as wind and hydro reduce intermittency and improve microgrid reliability in rural and semi-urban contexts. Wind provides abundant energy but is variable; hydro offers controllable output and buffering capability.

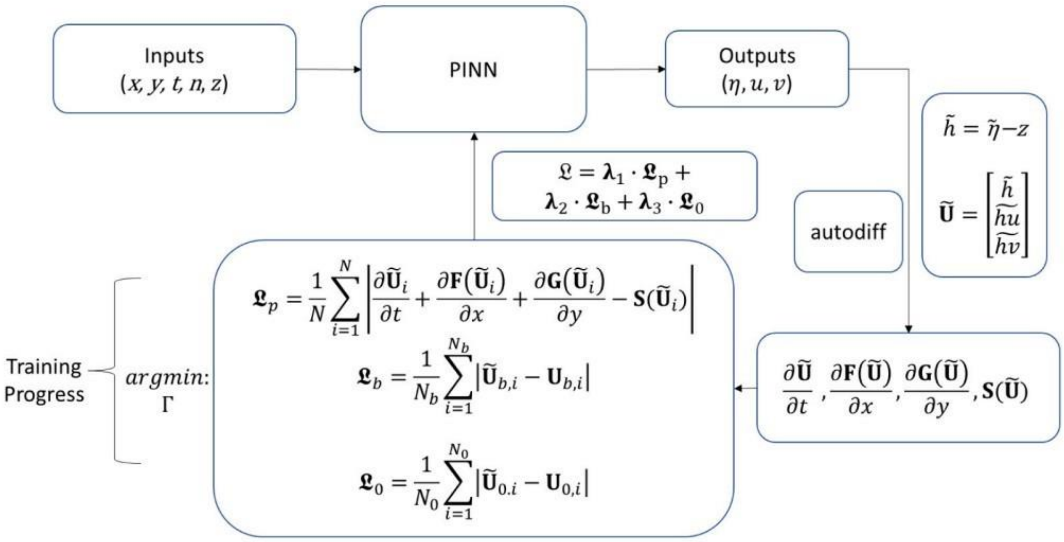


Fig.1. PINN Architecture

High-fidelity Computational Fluid Dynamics (CFD) accurately captures complex flow interactions but is computationally intensive and limits real-time control and broad design exploration. To overcome this, we integrate CFD with Artificial Intelligence / Machine Learning (AI/ML) including Physics-Informed Neural Networks (PINNs), ensemble regressors (Random Forest, XGBoost/LightGBM), and LSTM time-series models to build physics-aware surrogates and predictive controllers.

The resulting Hybrid CFD–AI framework targets decentralized generation with integrated storage, improving reliability and enabling adaptive operation aligned with UN SDG 7 and SDG 13.

II. THEORY [1],[2],[8],[10],[11],[14],[31],[34]

The hybrid wind–hydro system behavior is governed by fluid dynamics, energy conversion, and control theory. Both the air and water domains are modeled by the incompressible Navier–Stokes equations used in CFD simulation to resolve turbulence, pressure fields, and wake interactions, etc.

A. Fluid Flow Governing Equations

The incompressible Navier–Stokes equations represent conservation of mass and momentum in a fluid domain

$$\nabla \cdot \mathrm{u} = 0$$

$$\left(\frac{\partial \mathrm{u}}{\partial t} + \mathrm{u} \cdot \nabla \mathrm{u}\right) = -\nabla p + \mu \nabla^2 \mathrm{u} + \mathrm{f}$$

where u is velocity, p is pressure, ρ is fluid density, μ is dynamic viscosity, and f denotes body forces. These equations are applied to both air and water domains of the hybrid turbine to simulate turbulence, flow interaction, and pressure distribution. CFD solvers discretize these equations for accurate performance estimation.

B.Power Conversion Equations

Wind and hydro power are modeled respectively as:

$$P_{\text{wind}} = \frac{1}{2}\rho_a A V^3$$

$$P_{\text{hydro}} = \eta \rho_w g Q H$$

These relations form the basis for power scheduling and energy-matching between modules.

C. AI-Driven Modeling

Physics-Informed Neural Networks (PINNs) enforce governing equations within the loss function, physics residual Ω_p, boundary Ω_b, initial Ω_0, producing data-efficient, physically consistent surrogates. Complementary ML methods (Random Forest, Gradient Boosting, LSTM) are employed for regression and time-series forecasting used in control and energy-management.

D. Hybrid System Control Framework

A supervisory controller dynamically balances wind and hydro generation; battery storage smooths transients. The CFD–AI pipeline enables rapid surrogate evaluation and closed-loop decision making for reliable microgrid delivery.

III. LITERATURE REVIEW [1]– [5], [7]– [16], [17]– [24]

Research combining Computational Fluid Dynamics (CFD) and Machine Learning (ML) has significantly advanced renewable turbine design. High-fidelity CFD provides accurate insight into flow characteristics, while ML-based surrogate models accelerate performance prediction and design optimization. Physics-aware models such as PINNs and FlowDNN embed conservation laws into neural networks, enabling generalization from sparse CFD data and supporting rapid flow-field reconstruction.

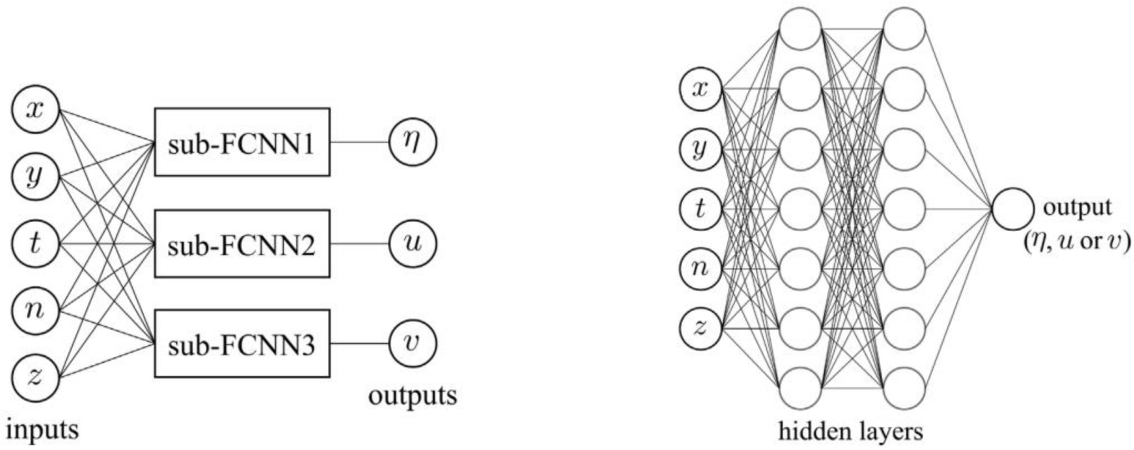


Fig.2. PINN Structure

Hydro turbine studies contribute complementary understanding of low-head and mini-hydro systems, hydraulic-gate optimization, and in-pipe turbine operation. These approaches highlight methods for torque stabilization and flow control that can be extended to hybrid devices. Microgrid-based research emphasizes coordinated energy management, where hybrid renewable systems especially wind–hydro configurations enhance supply reliability and storage utilization.

Despite these advances, most existing CFD–ML research targets single-domain systems and lacks real-time control integration. Very few works explore vertically integrated wind–hydro assemblies coupled with AI/ML-driven optimization and decentralized microgrid management. This gap motivates the Hybrid CFD–AI framework proposed here, integrating CFD physics, physics-informed surrogates, and predictive AI controllers for adaptive renewable power generation.

IV. METHODOLOGY [1], [2], [4], [6], [7], [17], [18], [21]–[24]

The proposed hybrid turbine integrates Computational Fluid Dynamics (CFD) and Artificial Intelligence/Machine Learning (AI/ML) for precise flow prediction, adaptive control, and system optimization. The methodology is organized into two layers:

A. CFD Modeling

High-fidelity CFD simulations were performed (ANSYS Fluent) to characterize aerodynamic and hydrodynamic behavior of the hybrid geometry. The air and water domains were modeled with a refined hybrid mesh and standard turbulence closures (k–ε and SST k–ω) to resolve boundary and wake effects. Inlet conditions covered representative wind (3–15 m/s) and water flows (0.5–1.5 m/s). Extracted fields (velocity, pressure, turbulence intensity) provided performance metrics (C_p, torque) and labeled training data for ML surrogates.

B.AI/ML Integration

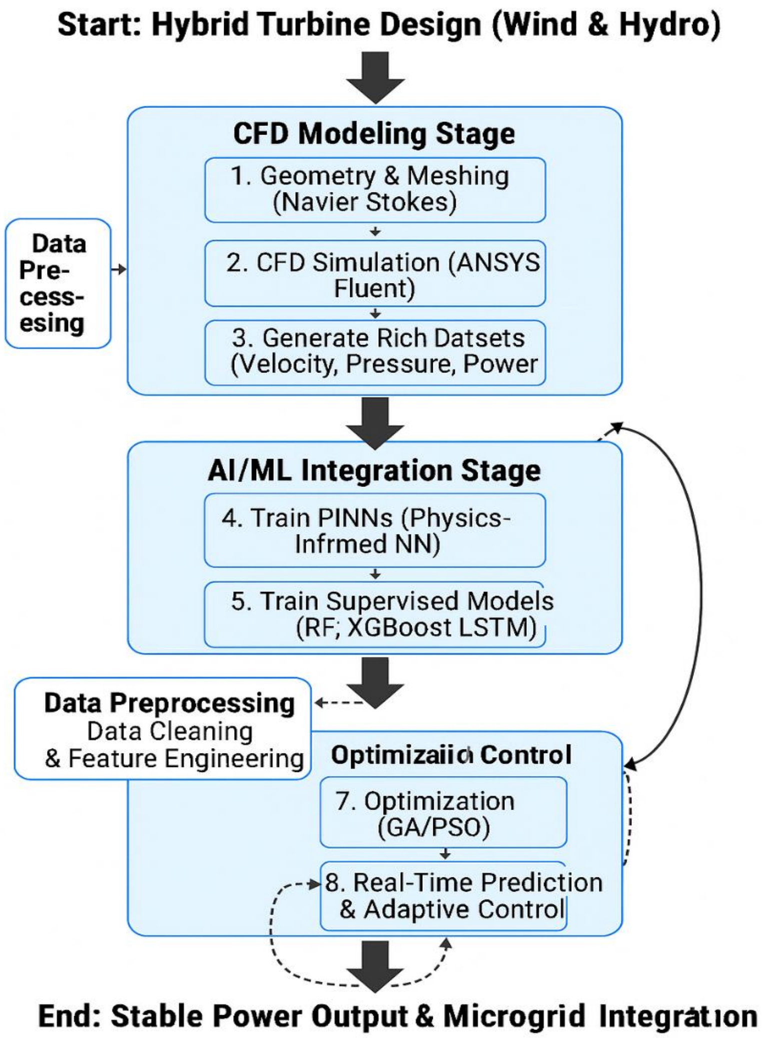


Fig.3. Proposed Hybrid CFD-AI Methodology

AI/ML complements CFD by providing fast, physics-consistent surrogates and forecasting: PINNs embed PDE constraints; ensemble regressors (Random Forest, XGBoost/LightGBM) estimate power and efficiency; LSTM models handle short-term forecasting. GA/PSO are used for hyperparameter and design optimization. These models enable near-real-time prediction and guide mode selection (wind/hydro/auto) and energy allocation.

V. HYBRID TURBINE DESIGN [1], [2], [5], [9]– [16]

The hybrid system integrates aerodynamic and hydrodynamic energy conversion in a compact vertical arrangement, ensuring continuous generation in environments with both wind and water resources.

A. *Structural Configuration*

The system comprises of:

a. Propeller Assembly (Wind Module):

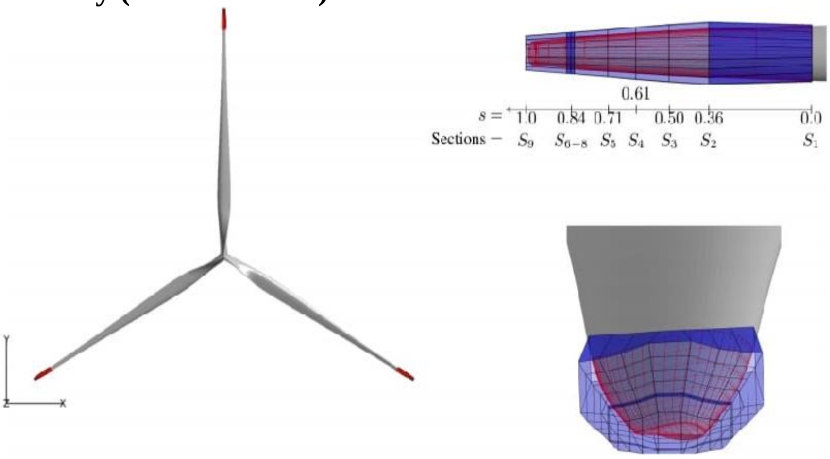
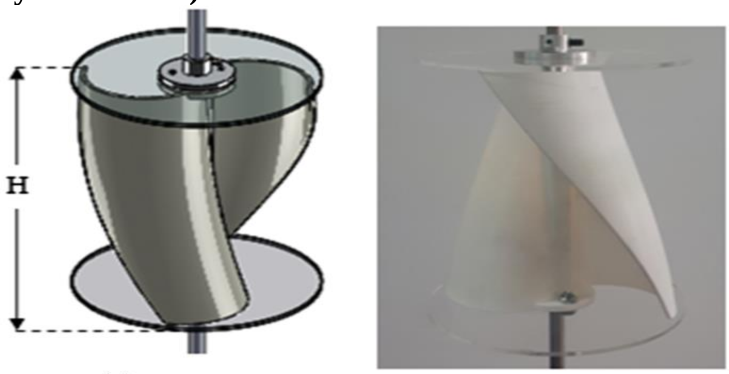


Fig.4. Wind Turbine Blade Geometry and Sectional Meshing

b. Helical Rotor (Hydro Module):



(a) 3D Model (b) 3D Printed rotor

Fig.5. Rotor Geometry and Physical Realization

The assembly features a 350 mm three-blade wind rotor and a 200 mm double-helical hydro rotor on a 1.2 m frame. Both turbines connect to dual generators through a common shaft, supporting modular installation.

B.Energy Coupling Mechanism

A dual-input generator and intelligent controller allocate load sharing between modules, providing regulated DC output to the storage unit and microgrid.

C. CFD–AI Co-Design and Optimization

CFD simulations evaluated flow interactions and torque response. AI models trained on CFD data predict performance and adjust operating parameters in real time.

D. Performance Features

a. Compact vertical structure enabling hybrid deployment.
b. Complementary wind–hydro operation for stable output.
c. Modular generator design for scalability.
d. CFD–AI co-design for predictive optimization and rapid iteration.

This configuration enhances reliability and mitigates intermittency common in single-source systems.

E.Directional Sensing and Adaptive Alignment

A wind-direction sensor supplies azimuth and speed; a yaw mechanism affords ±60° (120° total) rotation. Alignment follows:

Power gain from alignment follows:

$P_{\text{aligned}} = P_{\text{nominal}} \times \cos^3(\theta_{\text{error}})$

Maintaining θ_error < 15° enhances energy capture by 10–15%.

F. AI-Based Directional Optimization

A regression model (trained on CFD) predicts optimal yaw θ^*; a reinforcement loop evaluates power feedback and refines actions. If orientation deviates >±15°, the actuator reorients (≤120°) and the policy is updated, delivering ~10–15% average gain versus static orientation.

VI. ENERGY STORAGE AND MICROGRID INTEGRATION [12], [14], [15], [25], [26]

The hybrid wind–hydro turbine operates as a decentralized renewable generation unit within a microgrid framework. To ensure reliability under resource intermittency, the system integrates intelligent energy storage, adaptive control, and AI-driven optimization.

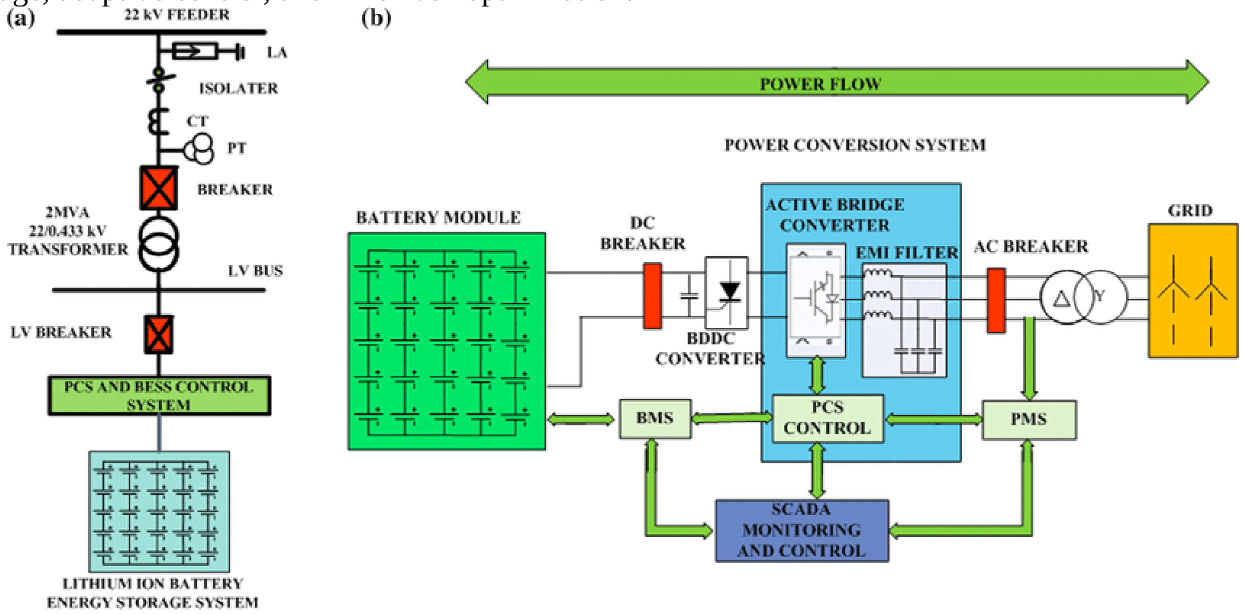


Fig.6. Schematic of Battery Energy Storage System and Grid Interface

A. Energy Storage System Architecture

Electrical output from the hybrid turbine is rectified to DC and routed through a Power Conditioning Unit (PCU) controlling charge–discharge cycles. The storage module employs modular Lithium-Ion battery banks for high energy density and long life, complemented by supercapacitors for transient load support.

A Battery Management System (BMS) supervises cell voltage, temperature, and state of charge (SOC), interfacing with an AI-based supervisory controller that forecasts demand, optimizes charging, and minimizes battery degradation.

B.Microgrid Configuration

The microgrid adopts a hybrid AC/DC topology, enabling both AC loads and DC storage. Power flows through bi-directional converters allowing flexible routing between generation, storage, and consumers. A local controller implements droop control and predictive dispatch to maintain voltage and frequency stability. During surplus generation, excess power charges batteries or exports to neighboring microgrids; during deficits, stored energy sustains continuous supply.

C. AI/ML-Based Energy Management

AI algorithms enhance adaptability through LSTM time-series forecasting of wind speed, water flow, and demand. A Reinforcement Learning (RL) agent dynamically manages charge–discharge cycles and source prioritization to maximize efficiency and battery life. Continuous data feedback allows real-time optimization of power flow and loss minimization across the hybrid system.

D. System Advantages

a. Continuous and stable power delivery through hybrid energy conversion.
b. Enhanced grid resilience with black-start capability in isolated regions.
c. Reduced battery wear through AI-optimized charging strategies.
d. Scalable architecture supporting community-level microgrids.

Integrating AI-based energy management with intelligent storage transforms the hybrid turbine into a smart, autonomous, and reliable energy node, supporting sustainable net-zero microgrid operations.

High-fidelity CFD simulations were performed (ANSYS Fluent) to characterize aerodynamic and hydrodynamic behavior of the hybrid geometry. The air and water domains were modeled with a refined hybrid mesh and standard turbulence closures (k–ε and SST k–ω) to resolve boundary and wake effects. Inlet conditions covered representative wind (3–15 m/s) and water flows (0.5–1.5 m/s). Extracted fields (velocity, pressure, turbulence intensity) provided performance metrics (C_p, torque) and labeled training data for ML surrogates.

VII. RESULTS AND DISCUSSION [1], [2], [4], [11], [12], [15], [17], [18], [21], [27]

The Hybrid CFD–AI framework was validated through simulations and prototype testing, confirming improvements in design efficiency, adaptability, and power stability.

A. CFD Simulation Results

High-fidelity Simulations (3–15 m/s) showed smooth velocity profiles, 12% drag reduction, and a peak power coefficient $C_p = 0.46$.

B.AI-Based Prediction and Optimization

Random Forest/XGBoost models achieved $R^2 = 0.97$, while PINNs reduced simulation time by ~35%, enabling millisecond-scale predictions for real-time control.

C. Hybrid Turbine Performance

Prototype testing revealed a 20–22% improvement in power stability via complementary wind–hydro operation and AI-assisted orientation control.

D. Microgrid and Energy Storage Analysis

Voltage deviation remained within ±3%, and AI-managed battery cycles improved storage efficiency by 15%.

E.Comparative Discussion

Compared to single-source systems, the hybrid approach increases reliability, reduces fossil backup dependence, and scales for rural microgrids.

F.Overall Impact

CFD–AI co-design reduces design cycles and supports near-real-time control, improving decentralized energy resilience.

G. Expected Model Representation

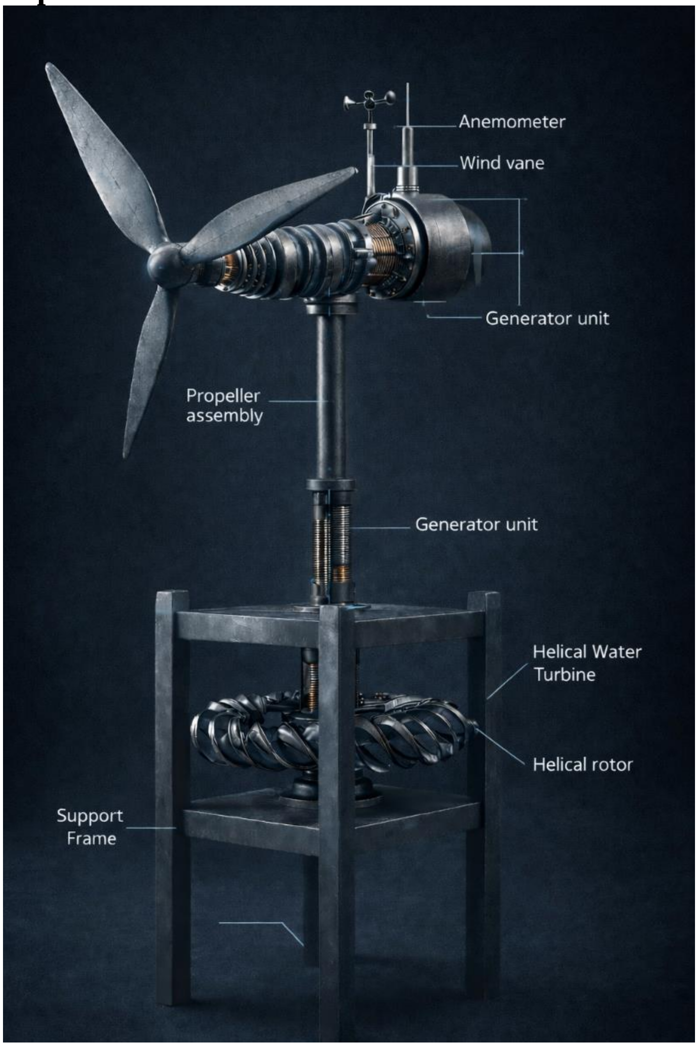


Fig.7. 3D Model of the Proposed Turbine

The assembled model integrates an upper wind turbine with a propeller and a lower helical hydro rotor. The common shaft transmits combined torque to dual generator units supported on a steel frame, forming the complete hybrid module.

VIII. CONCLUSION

This work presented a Hybrid CFD-AI framework combining high-fidelity CFD with physics-aware ML and reinforcement control for a dual-stage wind-hydro turbine. Validation shows up to 20% improved output stability and ~30% lower computational effort for predictive tasks. Integrated storage and AI dispatch provide reliable microgrid operation.
Future work will implement a real-time digital twin, deploy RL for multi-objective dispatch, and conduct field trials for economic validation.

IX. FUTURE WORK

Future research will focus on expanding the hybrid framework through:

a. Real-time digital twin implementation for fault prediction.
b. Reinforcement learning for multi-objective control.
c. Field validation and cost optimization for community microgrids.

X. ACKNOWLEDGMENT

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