

Background & Motivation

- Accurate PV performance prediction is essential for energy yield estimation, system optimization, and performance monitoring.
- Physics-based models exhibit systematic bias under real operating conditions. Thermal lag, spectral mismatch, and sensor uncertainty introduce residual errors that standard inputs cannot fully resolve.
- Unresolved bias undermines yield estimates and degrades confidence in model-based decision support
- Adaptive modeling frameworks are needed that preserve physical interpretability while learning from field data across varying levels of instrumentation availability.
- This work presents a **hybrid digital twin framework** coupling a single-diode physics model with an AI residual-correction layer:

$$P_{\text{hybrid}} = P_{\text{phys}} + \Delta P_{\text{AI}}$$

The framework is validated using DOE ARM CoURAGE field measurements at Morgan State University.

Research Objectives

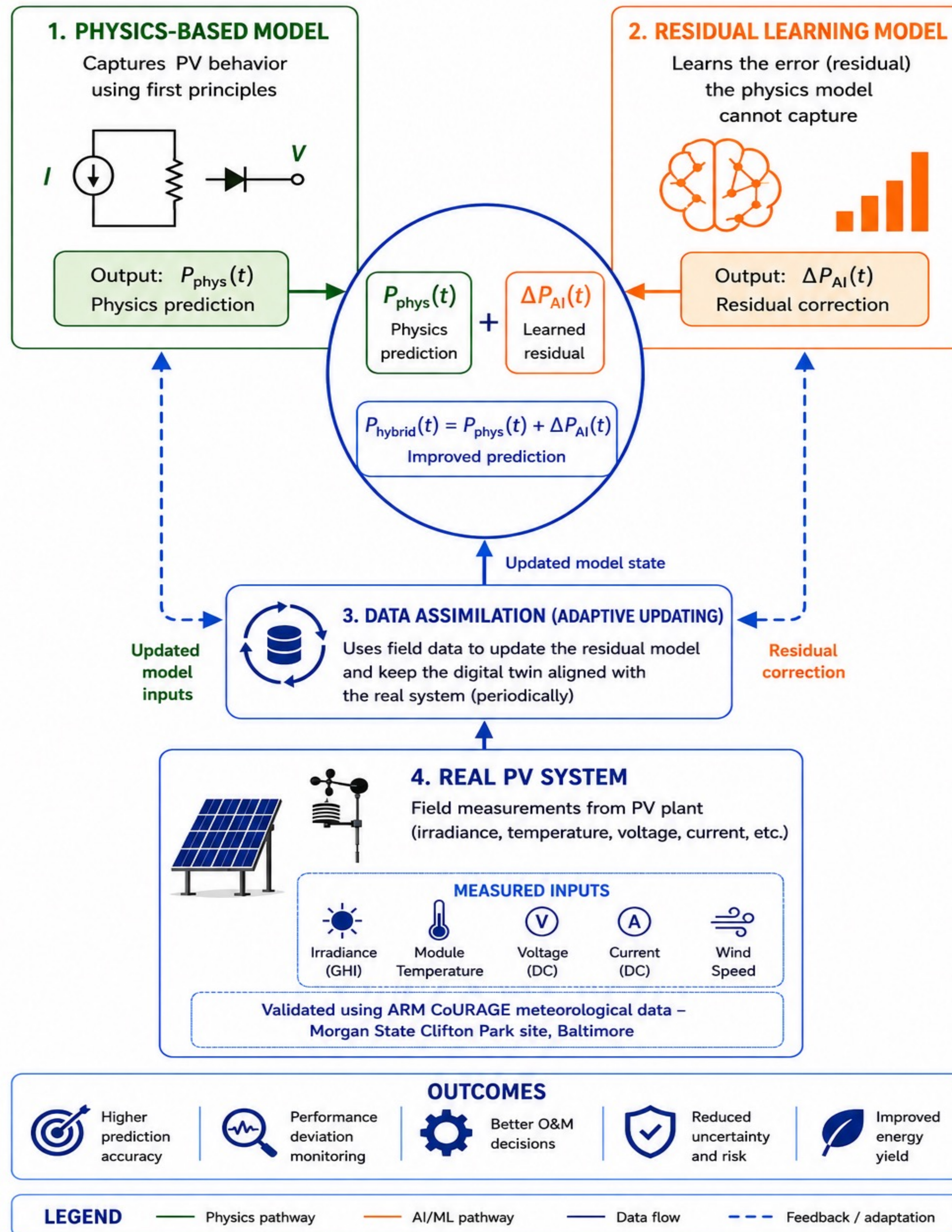
- Develop** A hybrid digital twin framework coupling a single-diode physics model with a machine-learning residual correction layer.
- Evaluate** the framework with POA irradiance + cell temperature under fixed-load conditions.
- Validate** The framework using 10,000+ field measurements from the DOE ARM CoURAGE facility at Morgan State University.
- Quantify** Prediction accuracy improvement of the hybrid model relative to the physics-only baseline.

Data & Experimental Setup

	PANEL	Silicon PV module deployed under fixed-load conditions
	SITE	DOE ARM CoURAGE Facility Morgan State University, Baltimore MD 39.31°N, 76.62°W
	INPUT	Irradiance & meteorological: ARM CoURAGE instrumentation Electrical: Voltage & current (custom DAQ)
	DATASET	10,000+ synchronized 1-minute observational records

Framework Architecture / Methodology

A physics-guided AI that learns and adapts using field data

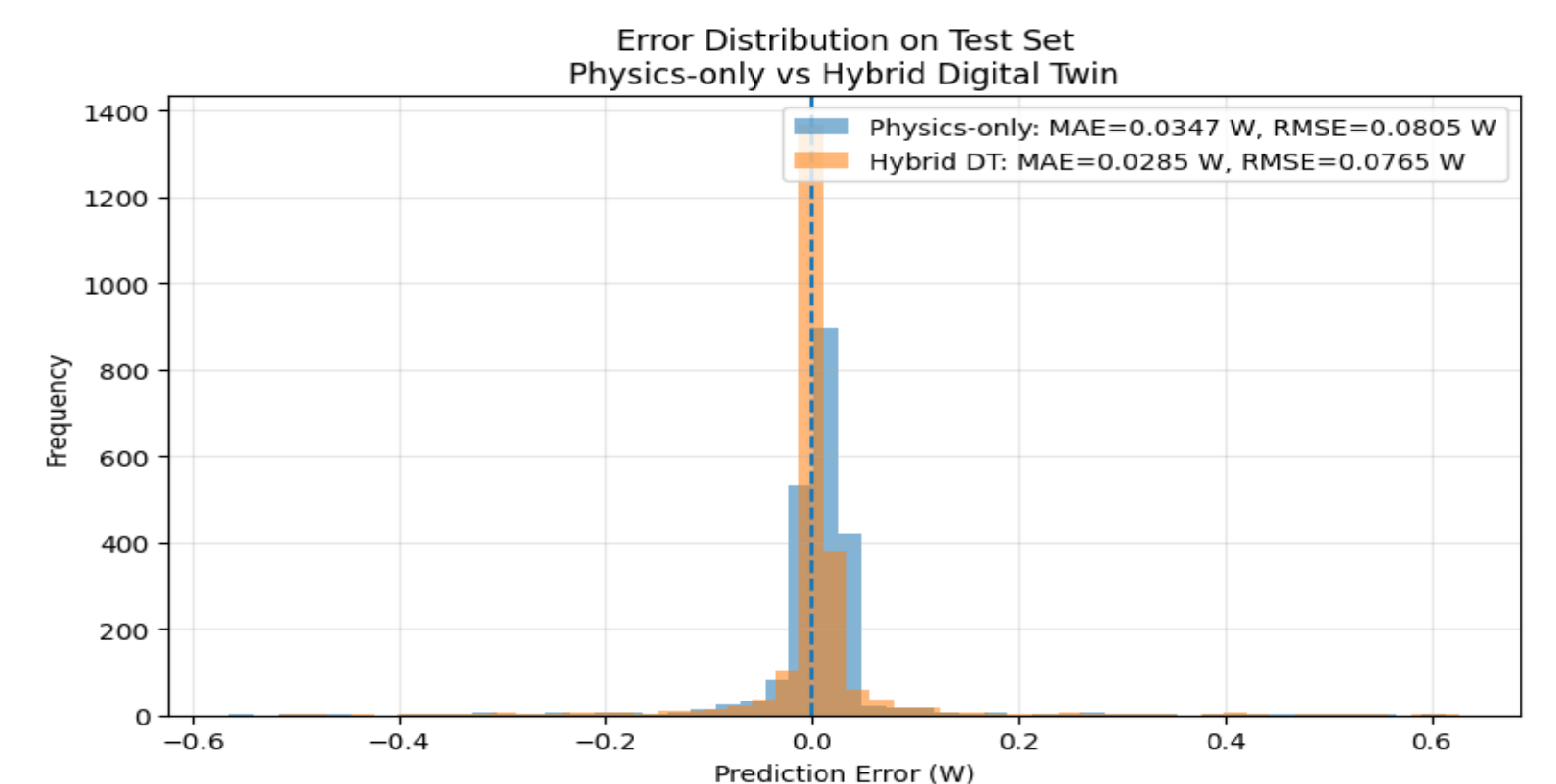
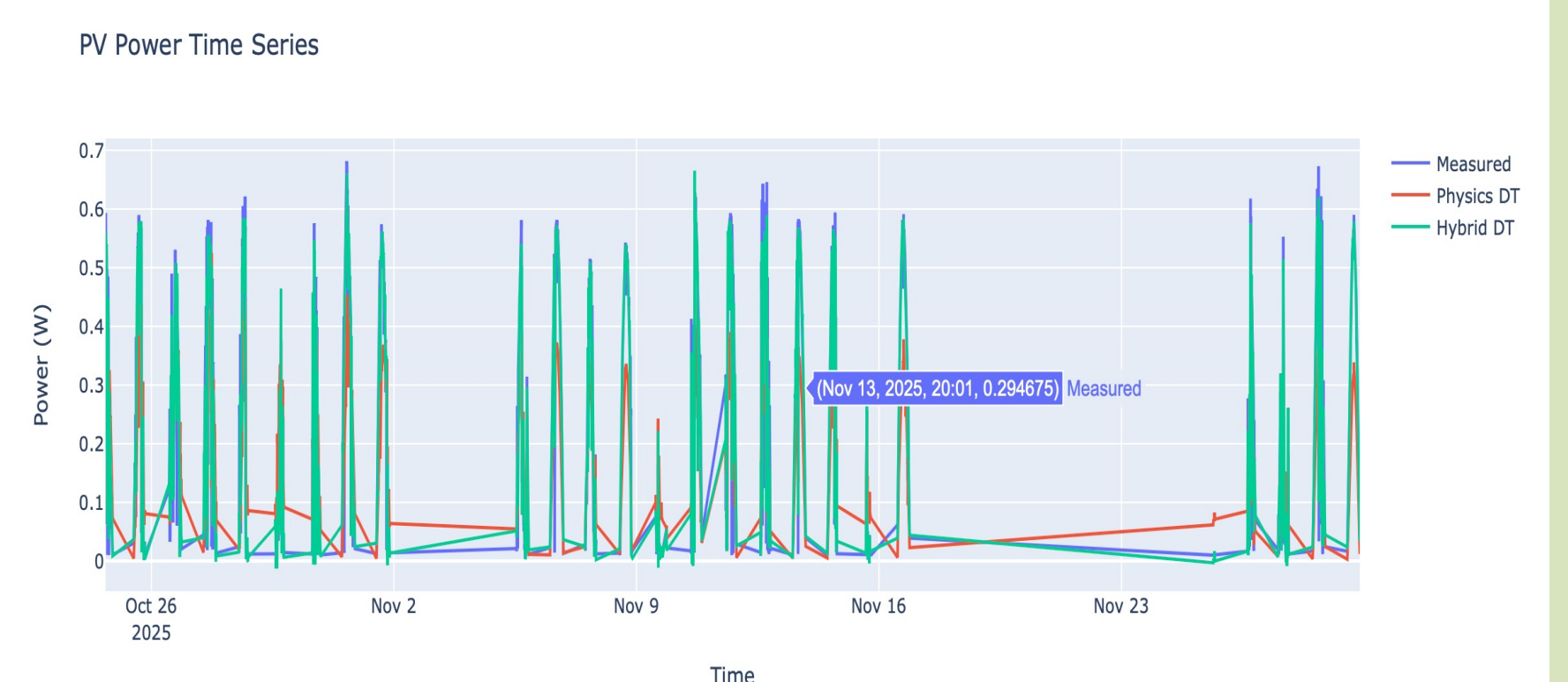
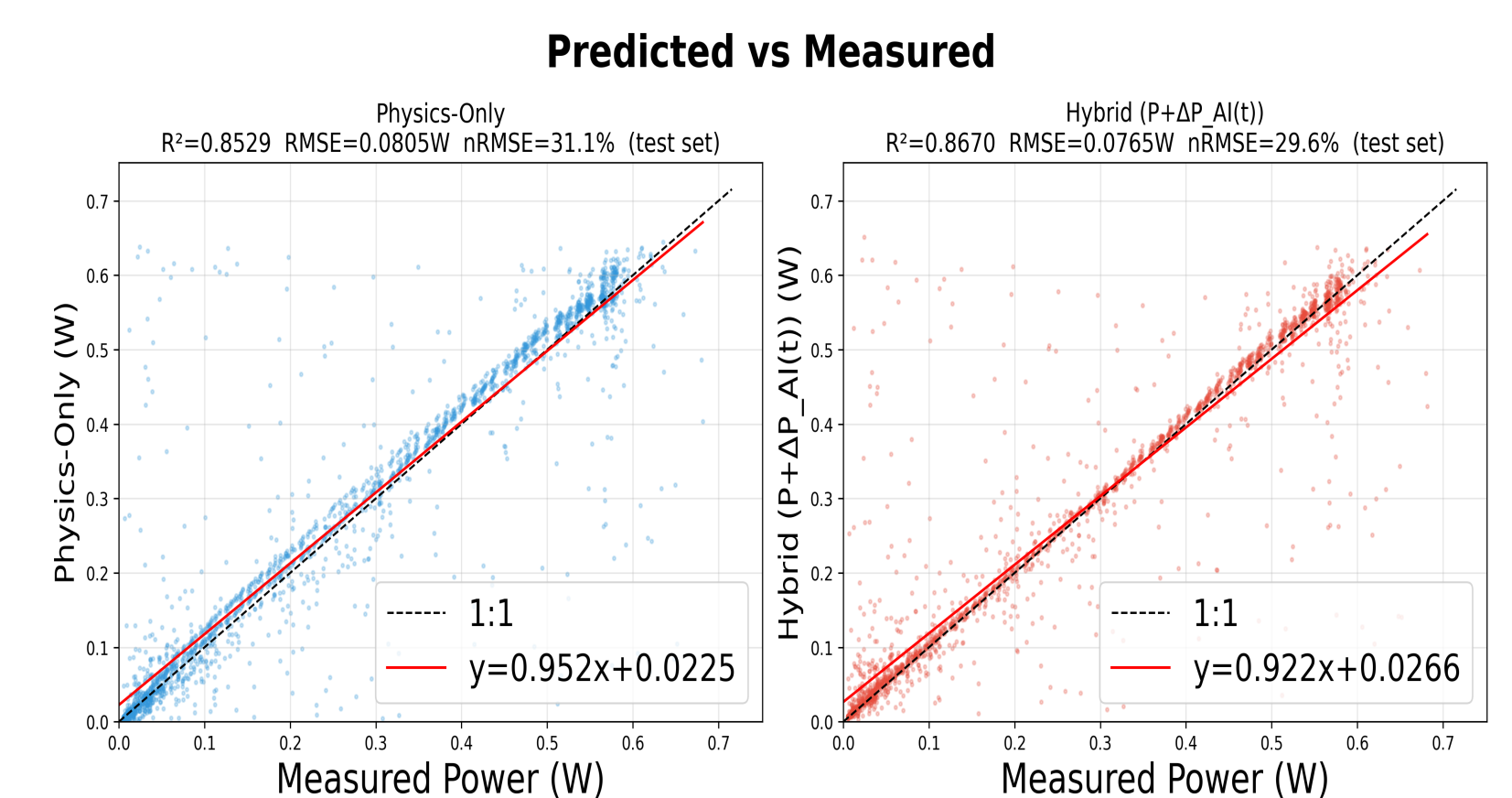


Preliminary Results & Discussion

POA + T_{cell} — MODEL PERFORMANCE COMPARISON

Model	MAE	RMSE	MBE	R ²	nRMSE
Physics-only	0.03472	0.08057	+0.00997	0.8526	31.20%
Hybrid DT	0.02869	0.07654	+0.00599	0.8669	29.68%

MAE REDUCTION	BIAS REDUCTION	R ² GAIN
17.4%	40.0%	+0.0143



Conclusions & Future Work

A hybrid digital twin coupling a single-diode physics model with AI residual correction was developed and field-validated. Validation against DOE ARM CoURAGE measurements demonstrated: MAE ↓ 17.4%, Bias ↓ 40.0%, R² improved from 0.8526 → 0.8669. DNI and short-term residual history emerged as dominant correction signals, indicating atmospheric spectral effects and thermal inertia as primary sources of residual error. Following abstract submission, the framework was refined to use POA irradiance and cell temperature instead of GHI and ambient temperature, improving physical fidelity and hybrid DT performance.

Future Work
Expand validation across seasonal conditions and additional ARM sites. Investigate continuous data assimilation using streaming field measurements. Extend the framework to utility-scale systems across diverse PV technologies and climate zones.

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References

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