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A Digital Twin Framework for Renewable Energy Education: A Work-in-Progress Study

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WIP: A Digital Twin Framework for Renewable Energy Education

Abstract

This work-in-progress paper presents the design and early implementation of a Digital Twin (DT) framework to support active, inquiry-based learning of photovoltaic (PV) systems within renewable energy education. The DT is directly linked to a laboratory-scale physical PV system through time-synchronized electrical and environmental measurements. This enables students to engage with authentic system behavior rather than idealized data and investigate how PV performance responds to changing operating conditions.

The framework integrates a hybrid DT architecture that combines a physics-based single-diode PV model with an AI-enhanced residual learning layer implemented using a Histogram Gradient Boosting regressor. This approach preserves physical interpretability while improving predictive accuracy by learning systematic discrepancies between modeled and measured performance. Using real sensor data, the hybrid DT achieved substantially improved agreement with measured power output (MAE = 0.0262, RMSE = 0.0525, $R^2 = 0.9337$) compared to the physics-only model (MAE = 0.1203, RMSE = 0.1415, $R^2 = 0.5175$), providing early technical validation of the modeling approach.

The DT is deployed through an interactive, browser-based dashboard that serves as the primary learning interface. Instructional integration includes pre-lab preparation, guided dashboard-based exploration, and post-lab reflection activities designed to emphasize conceptual reasoning, model comparison, and data literacy rather than algorithmic detail. Preliminary qualitative evidence from post-lab surveys suggests that students were able to distinguish physics-based and hybrid models, reason about model accuracy and limitations, and engage meaningfully with model–data comparisons.

This work contributes a replicable DT-enabled instructional framework that tightly couples real experimental data, hybrid modeling, and inquiry-driven learning activities, advancing digital twin pedagogy for renewable energy education and aligning with the Data Science and Artificial Intelligence (DSAI) Committee’s emphasis on data-informed and AI-enabled engineering learning.

Keywords: Digital Twin, Photovoltaic Education, Artificial Intelligence, Hybrid Modeling, Experiential Learning, Engineering Education

1. Introduction

Preparing engineers to design, operate, and optimize renewable energy systems is critical to achieving global sustainability goals [1][2]. Global installed renewable capacity reached 4,448 GW in 2024, representing a 15.1% expansion led by solar photovoltaics and wind. Targets aim to triple capacity to 11.17 TW by 2030 [3]. This rapid growth intensifies demand for engineers equipped not only with strong foundations in renewable energy technologies but also with competencies in data analytics, artificial intelligence (AI), and digitalization tools [4][5].

Education plays a pivotal role in meeting this demand [6], and the International Renewable Energy Agency, through its Energy Transition Education Network (ETEN), emphasizes the need for modernized educational strategies to scale up renewable-energy training worldwide [7].

Yet significant disparities persist. Many engineering programs—particularly in under-resourced institutions and economically disadvantaged regions—rely heavily on traditional, theory-centric instruction [8][9]. Students frequently learn photovoltaic (PV) concepts without adequate exposure to hands-on experimentation, real-time system behavior, or data-driven modeling practices. This inequity in access to modern learning tools risks producing graduates insufficiently prepared for the cyber-physical, data-intensive, and AI-enabled technologies defining Industry 4.0 and the emerging clean-energy sector. Addressing this gap requires innovative, accessible educational frameworks that integrate live data, intelligent modeling, and interactive learning environments — tools that can democratize exposure to authentic engineering practice regardless of institutional resources.

Virtual laboratories and simulation tools such as PVsyst, SAM, and MATLAB/Simulink have long enhanced renewable energy education by supporting remote experimentation, parameter variation, and visualization of complex PV behavior [10][11]. However, these tools typically operate independently of physical hardware and rely on idealized or predefined datasets [12]. This limits their ability to reproduce the variability, noise, and nonideal operating conditions that characterize actual systems.

Digital Twin (DT) technology offers a promising solution. A DT is a virtual representation of a physical system continuously linked to its real-world counterpart through data streams [13][14]. Table 1 summarizes key distinctions between simulation tools, virtual laboratories, and digital twins for engineering education. By integrating measured data into the digital model, DTs enable students to observe how environmental variations and nonideal conditions influence performance, compare measurements with predictions, and diagnose discrepancies. Photovoltaics, as one of the fastest growing and most accessible renewable technologies, represents an ideal context for this approach [15]. Importantly, browser-based DT implementations can extend these capabilities to institutions lacking expensive laboratory infrastructure, potentially narrowing the educational equity gap in renewable energy training [16].

Table 1. Comparison of educational approaches for PV systems learning.

Dimension	Simulation Tools	Virtual Labs	Digital Twins
Physical System Link	None	None or indirect	Direct, real-time
Data Source	Synthetic/idealized	Predefined datasets	Measured sensor data
Real-World Variability	Limited	Limited	Present (noise, nonidealities)
Model Validation	Against benchmarks	Rare	Measured vs. modeled comparison
Accessibility	Licensed software	Institution-dependent	Browser-based (low barrier)

This work-in-progress study explores how a Digital Twin framework can support photovoltaic system learning through three research questions:

- **RQ1:** How can a Digital Twin framework integrating physical system modeling and data-driven components be designed to support PV learning?
- **RQ2:** How can a digital twin framework support active, inquiry-based learning of PV behavior under realistic environmental variability?
- **RQ3:** What preliminary learning and engagement outcomes are observed when students use a DT-based PV learning module?

As a work-in-progress, this study makes two primary contributions to renewable energy education. First, we propose a hybrid Digital Twin framework for photovoltaic learning that integrates physics-based modeling with AI-enhanced residual learning, implemented as an interactive browser-based dashboard and supported by a structured instructional sequence grounded in experiential and inquiry-based principles. Second, we report preliminary observations from student engagement with the framework, offering initial evidence to inform future refinement and more comprehensive evaluation.

2. Digital Twin Framework Design

This section addresses RQ1 by describing a work-in-progress hybrid Digital Twin framework for photovoltaic (PV) education. The framework integrates real sensor data from a physical PV module, a physics-based model, and a data-driven residual learning component into an interactive dashboard supporting inquiry-based learning. Figure 1 illustrates an architectural overview.

The Hybrid Digital Twin Architecture

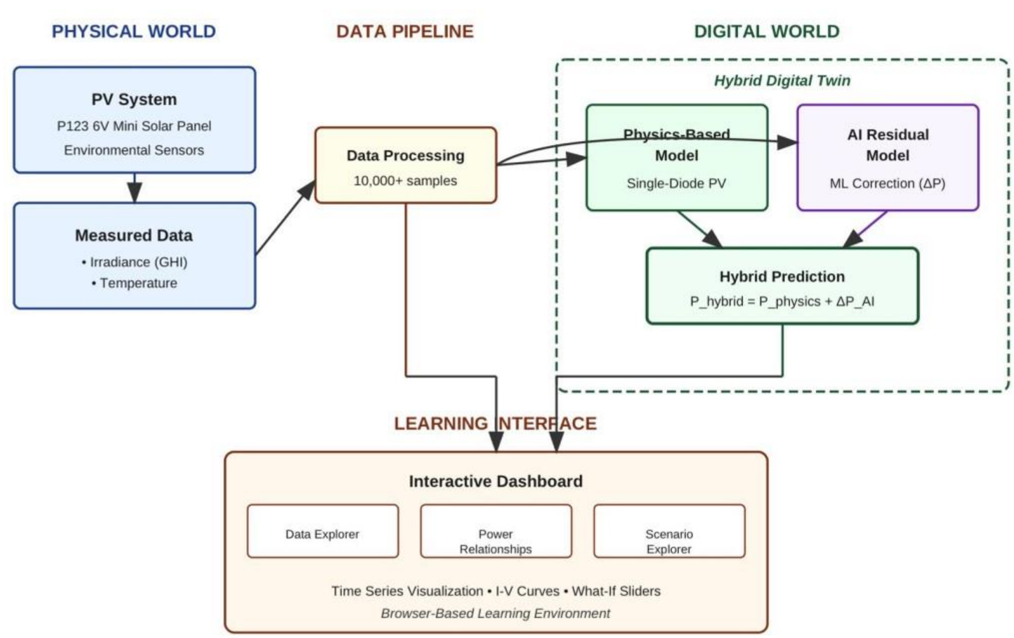


Figure 1. Hybrid Digital Twin framework integrating physical PV system, modeling layers, and browser-based learning interface.

2.1 Physical System and Data Pipeline

The physical system consists of a P123 6V mini solar panel deployed at an Atmospheric Radiation Measurement (ARM) site, instrumented to collect time-stamped measurements of electrical output (voltage, current) and environmental conditions including global horizontal irradiance (GHI) and ambient temperature. Measured power is computed as $P_{meas}(t) = V(t) * I(t)$. The dataset comprises over 10,000 measurements collected during October–November 2025.

Data quality procedures included removing invalid records, enforcing physical bounds on measurements, filtering low-irradiance periods, and preserving temporal structure for time-aware model development.

Educational rationale: Integrating cleaned measurements from an operational PV system provides students with access to real-world variability rarely available in traditional simulationbased laboratories.

2.2 Digital System Architecture

The Digital Twin comprises three layers: physics-based modeling, AI-enhanced residual learning, and hybrid integration (Figure 1).

Physics-Based Layer. The physics-base model uses a simplified single-diode formulation with irradiance and temperature inputs to estimate power: $P_{phys}(t) = f_{phys}(G(t), T(t))$. Model parameters ($I_{ph}$, I_O, R_s, R_{sh}, a) were extracted from manufacturer specifications and calibration data. This approach offers transparency for instructional purposes, though simplifying assumptions can result in mismatches with measured behavior.

AI-Enhanced Residual Layer. A Histogram Gradient Boosting Regressor, selected for its robustness and computational efficiency, learns systematic discrepancies between physics predictions and measurements, outputting a correction term $\hat{r}_{AI}(t)$. The model was trained on 80% of the data and validated on a held-out 20% subset. This layer captures effects the physics model cannot represent, including sensor noise and operational nonidealities.

Hybrid Integration. The hybrid Digital Twin combines both layers: $P_{DT}(t) = P_{phys}(t) + \hat{r}_{AI}(t)$. This architecture balances interpretability with predictive accuracy. Evaluation against 10,000+ measured data demonstrated that the hybrid model substantially outperformed the physics-only model (Table 2), validating the framework's technical foundation before educational deployment.

Table 2: Model performance comparison against measured power (n = 10,000+ samples)

Model	MAE (W)	RMSE (W)	R^2
Physics-Based DT	0.120	0.142	0.52
Hybrid DT	0.026	0.053	0.93

Educational rationale: Students observe where physics-based assumptions break down and how data-driven methods complement first-principles modeling—developing engineering judgment about model accuracy and limitations.

Model performance was evaluated using MAE, RMSE, and R^2, metrics also presented to students to support comparison and interpretation.

2.3 Learning Interface

The framework uses a browser-based interactive dashboard as the primary learning interface. The dashboard is organized into three student-facing tabs (see Appendix II for screenshots):

- Data Explorer: Time-series comparison of measured, physics-based, and hybrid outputs with error metrics.
- Power Relationships: Binned visualizations of power versus irradiance and temperature.
- Scenario Explorer: What-if analysis through adjustment of environmental inputs**.**

The browser-based implementation requires no specialized software installation or institutional hardware infrastructure. Students can access the dashboard via any device with a web browser, supporting scalability and adoption across diverse learning environments.

3. Instructional Use and Learning Design

3.1 Learning Goals

The Digital Twin framework supports inquiry-based learning of PV system behavior under realistic conditions. Students are expected to (i) reason about relationships between environmental variables and power output, (ii) compare physics-based and hybrid modeling approaches, and (iii) reflect on model assumptions and limitations. Unlike static simulations, the framework integrates authentic measured data, exposing students to real-world variability as a learning opportunity. The emphasis on conceptual reasoning and model literacy makes the framework appropriate for undergraduate and early graduate learners.

3.2 Pedagogical Framing

The design draws on inquiry-based learning [17][18][19] and Kolb's experiential learning cycle [20]. As shown in Figure 2, the three-phase instructional sequence aligns with this cycle: pre-lab activates prior knowledge, the lab activity provides concrete experience and active experimentation, and post-lab supports reflective observation and abstract conceptualization. *3.3 Instructional Sequence*

Instructional Sequence of Digital Twin Learning Module

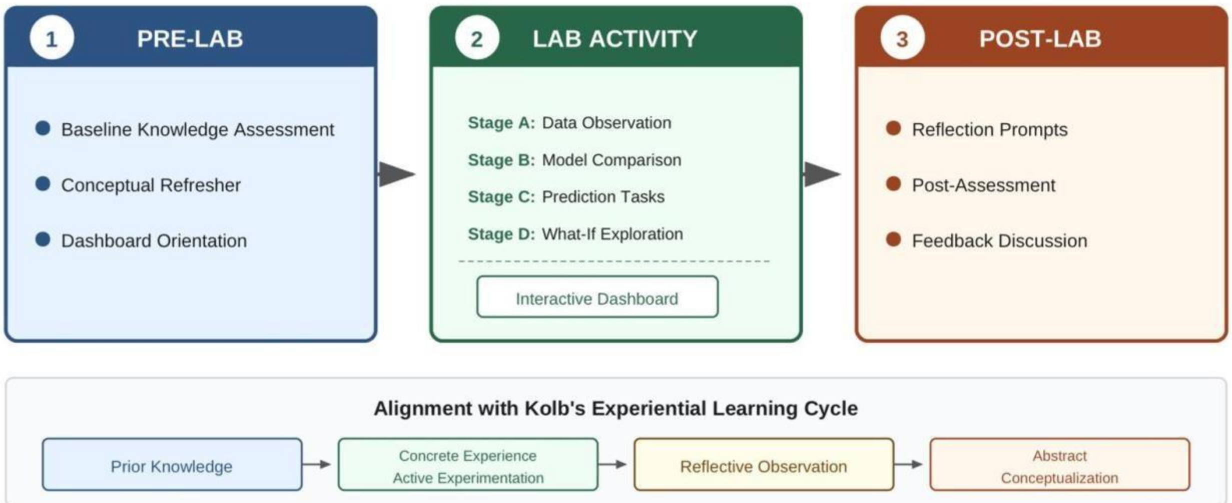


Figure 2. Instructional sequence of the Digital Twin learning module with alignment to Kolb's experiential learning cycle.

Pre-Lab. Baseline assessment and conceptual refresher establish common ground before dashboard engagement.

Lab Activity. Students interact with the dashboard through guided tasks: exploring measured data alongside model predictions, comparing trends, and investigating discrepancies. Activities emphasize comparison and explanation rather than numerical optimization.

Post-Lab. Reflection prompts capture how students interpret model behavior and articulate limitations.

3.4 Dashboard Design

The dashboard introduces progressive complexity through three components:

- Data Explorer: Time-series comparison of measured, physics-based, and hybrid predictions with error metrics (MAE, RMSE, R^2).
- Power Relationships: Binned-mean trends versus irradiance and temperature with filtering to isolate variable effects.
- Scenario Explorer: What-if analysis via adjustable sliders to test hypotheses about environmental effects.

This progression moves students from observation to analysis to prediction. Refinements to this sequence will be informed by pilot feedback.

4. Implementation and Student Engagement

Five undergraduate and early graduate ECE students voluntarily participated in a formative pilot evaluation of the Digital Twin dashboard. Prior coursework in renewable energy was not required, enabling observation of how students with varied backgrounds engaged with the module. The first author served as facilitator. The module is intended for upper-level undergraduate or introductory graduate courses in renewable energy or power systems, consistent with typical class sizes of 15–30 students at the institution.

Pre-Lab. Students completed a brief online pre-assessment (~10 min, Appendix I) followed by a conceptual refresher session (~40 min) covering PV fundamentals, modeling concept and basic data literacy.

Lab Activity. Students accessed the browser-based dashboard independently and worked through guided prompts (Appendix III) at their own pace. Facilitation emphasized prompting explanation rather than providing answers. Students engaged with three dashboard components:

- *Data Explorer:* Selecting time windows to compare measured power against physicsbased and hybrid predictions, relating visual patterns to error metrics (MAE, RMSE, R^2).
- *Power Relationships:* Investigating binned relationships between power, irradiance, and temperature using filters to isolate variable effects.
- *Scenario Explorer:* Conducting what-if analyses by adjusting environmental sliders to compare predictions under hypothetical conditions.

All five students completed the full activity sequence.

Post-Lab. Students completed an online reflection and assessment (Appendix III) capturing perceived learning gains and engagement.

5. Preliminary Observations and Findings

This section reports observations from five students who interacted with the Digital Twin dashboard.

Conceptual Understanding. Post-lab responses indicated that all five students (100%) correctly identified the key difference between modeling approaches, selecting "The Physics DT uses basic physics equations, while the Hybrid DT improves the result using AI." After the activity, 80% rated their understanding of how Digital Twins can study PV systems as high or very high.

Model Comparison and Visualization. Students responded positively to the time-series comparison feature: 80% strongly agreed and 20% agreed that the plot "helped me understand when and why model predictions differ from real PV behavior." One student noted: "Having both the physics and hybrid digital twin being plotted alongside the measured data put into context the performance of each twin." Another observed "how there is an effect in the PV with respect to the daytime."

Engagement. Compared to traditional labs, 40% rated the activity as extremely engaging and 40% as moderately engaging. One student described the dashboard as "a good platform to help visualize and corroborate this engineering phenomenon."

Suggested Improvements. Students identified areas for refinement: contextual descriptions for novice users, enhanced graphics, and time-of-day indicators. One suggested "small descriptions for the different explorers... for someone who may be new to solar energy."

These observations suggest that the Digital Twin framework may support conceptual understanding and engagement among students with varied backgrounds. Systematic evaluation with larger cohorts and formal pre–post assessments is planned.

6. Discussion, Limitations, and Future Work

Discussion. The preliminary observations suggest that the hybrid Digital Twin framework may support conceptual understanding of PV system behavior among students with varied backgrounds. The 100% correct response rate on distinguishing physics-based from hybrid models indicates students grasped the core pedagogical concept. Positive engagement ratings and student reflections—particularly around visualizing model-data comparisons—align with the framework design intent grounded in experiential and inquiry-based learning principles. The substantial performance difference between models ($R^2 = 0.93$ vs. 0.52) provided students with concrete, observable evidence of how data-driven methods complement first-principles modeling.

Limitations. This work-in-progress has several limitations: (1) small sample size (n=5) precludes generalization; (2) absence of pre-post comparison limits claims about learning gains; (3) single institution and single facilitator (first author) may introduce potential bias, as facilitator involvement could have influenced student engagement, and future studies will employ standardized facilitation protocols; (4) self-paced activity was not timed, limiting reproducibility analysis.

Future Work. Planned extensions include: (1) deployment with larger, more diverse cohorts across multiple institutions; (2) formal pre-post assessments to measure learning gains; (3) controlled comparisons with traditional simulation-based instruction; (4) refinement of the dashboard based on student feedback, including contextual help features and time-of-day indicators; and (5) expansion of the framework to other renewable energy systems such as wind or battery storage; and (6) targeted assessment of higher-order competencies such as systems thinking, fault diagnosis, and model-based problem-solving.

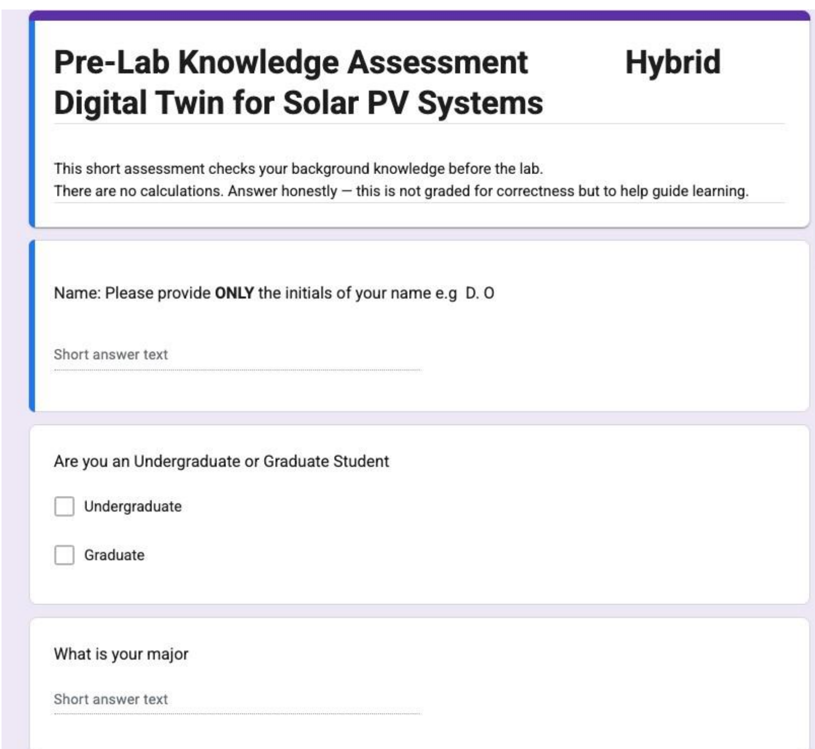
References

[1] C. I. Davidson *et al.*, "Preparing future engineers for challenges of the 21st century: Sustainable engineering," *Journal of Cleaner Production*, vol. 18, no. 7, pp. 698–701, May 2010, doi: 10.1016/j.jclepro.2009.12.021.
[2] N. Singh, R. Nyuur, and B. Richmond, "Renewable Energy Development as a Driver of Economic Growth: Evidence from Multivariate Panel Data Analysis," *Sustainability*, vol. 11, no. 8, p. 2418, Apr. 2019, doi: 10.3390/su11082418.
[3] "Renewable Capacity Highlights 2025".
[4] S. Jafarinejad, L. E. Beckingham, M. Kathe, and K. Henderson, "The Renewable Energy (RE) Industry Workforce Needs: RE Simulation and Analysis Tools Teaching as an Effective Way to Enhance Undergraduate Engineering Students' Learning," *Sustainability*, vol. 13, no. 21, p. 11727, Oct. 2021, doi: 10.3390/su132111727.
[5] "Renewable energy and jobs: Annual review 2024".
[6] B. Gilmour, "An award winning approach to education relating to renewable energies," in *2022 7th International Conference on Environment Friendly Energies and Applications (EFEA)*, Bagatelle Moka MU, Mauritius: IEEE, Dec. 2022, pp. 1–5. doi: 10.1109/EFEA56675.2022.10063830.
[7] S. Elsayed, "Education for the Energy Transition".
[8] B. Y. Toh and N. Buchanan, "Portable, Inclusive, and Affordable Electronics Laboratories: Promoting Diversity and Overcoming Barriers in Engineering Education," in *2025 IEEE Global Engineering Education Conference (EDUCON)*, London, United Kingdom: IEEE, Apr. 2025, pp. 1–6. doi: 10.1109/EDUCON62633.2025.11016552.
[9] M. Kar, "Equitable STEM Education for Underserved Communities: Implementing Effective Learning Methodologies," in *2024 IEEE Global Engineering Education Conference (EDUCON)*, Kos Island, Greece: IEEE, May 2024, pp. 01–03. doi: 10.1109/EDUCON60312.2024.10578750.
[10] L. Guo, N. M. M. Abdul, M. Vengalil, K. Wang, and A. Santuzzi, "Engaging Renewable Energy Education Using a Web-Based Interactive Microgrid Virtual Laboratory," *IEEE Access*, vol. 10, pp. 60972–60984, 2022, doi: 10.1109/ACCESS.2022.3181200.
[11] A. Witzig, A. Wolf, L. Kunath, A. Alyaseen, and R. Axthelm, "Teaching Renewable Energy Systems by Use of Simulation Software: Experience At Universities of Applied Sciences, in In-Service Training, and from International Know-How Transfer," in *Proceedings of EuroSun2016*, Palma de Mallorca, Spain: International Solar Energy Society, 2016, pp. 1–10. doi: 10.18086/eurosun.2016.10.03.
[12] L. Wright and S. Davidson, "How to tell the difference between a model and a digital twin," *Adv. Model. and Simul. in Eng. Sci.*, vol. 7, no. 1, p. 13, Dec. 2020, doi: 10.1186/s40323-020-00147-4.
[13] G. Cao and J. Bai, "Design Optimisation and Implementation of an Industrial Robot System Based on Digital Twin Technology," in *2024 4th International Conference on Machine Learning and Intelligent Systems Engineering (MLISE)*, Zhuhai, China: IEEE, Jun. 2024, pp. 461–464. doi: 10.1109/MLISE62164.2024.10674459.
[14] O. Olayiwola, U. Cali, M. Elsden, and P. Yadav, "Enhanced Solar Photovoltaic System Management and Integration: The Digital Twin Concept," *Solar*, vol. 5, no. 1, p. 7, Mar. 2025, doi: 10.3390/solar5010007.
[15] G. M. Wilson *et al.*, "The 2020 photovoltaic technologies roadmap," *J. Phys. D: Appl. Phys.*, vol. 53, no. 49, p. 493001, Dec. 2020, doi: 10.1088/1361-6463/ab9c6a.

[16] C. Palmer *et al.*, “Digital Twinning remote laboratories for online practical learning,” *Production & Manufacturing Research*, vol. 10, no. 1, pp. 519–545, Dec. 2022, doi: 10.1080/21693277.2022.2097140.
[17] M. Prince, “Does Active Learning Work? A Review of the Research,” *J of Engineering Edu*, vol. 93, no. 3, pp. 223–231, Jul. 2004, doi: 10.1002/j.2168-9830.2004.tb00809.x.
[18] M. Prince and M. Vigeant, “Using Inquiry Based Activities To Promote Understanding Of Critical Engineering Concepts,” in *2006 Annual Conference & Exposition Proceedings*, Chicago, Illinois: ASEE Conferences, Jun. 2006, p. 11.1390.1-11.1390.14. doi: 10.18260/12--808.
[19] B. L. M. Levy, E. E. Thomas, K. Drago, and L. A. Rex, “Examining Studies of InquiryBased Learning in Three Fields of Education: Sparking Generative Conversation,” *Journal of Teacher Education*, vol. 64, no. 5, pp. 387–408, Nov. 2013, doi: 10.1177/0022487113496430.
[20] “Experiential Learning Theory.pdf.”

Appendix

Appendix I – Pre-Lab Assessment



Pre-Lab Knowledge Assessment Hybrid Digital Twin for Solar PV Systems

This short assessment checks your background knowledge before the lab.
There are no calculations. Answer honestly — this is not graded for correctness but to help guide learning.

Name: Please provide **ONLY** the initials of your name e.g D. O

Short answer text

Are you an Undergraduate or Graduate Student

☐ Undergraduate

☐ Graduate

What is your major

Short answer text

Section A: Foundational Physics & Energy Concepts

1. A solar panel produces electricity in the form of **voltage and current**. Which statement sounds most reasonable?

- [ ] Only voltage matters
- [ ] Only current matters
- [ ] Both voltage and current matter for power
- [ ] Neither matter

2. Increasing solar irradiance (sunlight intensity) generally causes PV power to:

- [ ] Decrease
- [ ] Remain Constant
- [ ] Increase
- [ ] Become Unpredictable

3. On a very **hot sunny day**, how do you think temperature affects solar panel performance?

- [ ] Hotter panels always produce more power
- [ ] Temperature has no effect
- [ ] High temperatures may reduce performance
- [ ] Panels stop working when hot

Section B: Concept of Models and Assumptions

4. A model in engineering is best described as:

- [ ] An exact copy of the real system
- [ ] A simplified representation based on assumptions
- [ ] A machine learning algorithm
- [ ] A simulation without equations

5. Which is an example of a modeling assumption?

- [ ] Sensors produce noise-free data
- [ ] Temperature affects PV performance
- [ ] Power is measured directly
- [ ] Voltage varies with current

6. What happens if a model's assumptions do NOT match real-world conditions?

- [ ] The model becomes more accurate
- [ ] The model results may become unreliable
- [ ] The model automatically corrects itself
- [ ] Nothing changes

7. A **Digital Twin** is best described as:

- [ ] A computer game
- [ ] A digital copy that represents how a real system behaves
- [ ] A physical sensor
- [ ] A spreadsheet of measurements

Section C: Basic Data Literacy

8. What does a dataset usually represent in an engineering experiment?

- [ ] A single measurement
- [ ] A collection of related measurements recorded over time or conditions
- [ ] A mathematical equation
- [ ] A simulation result only

9. Why do engineers remove nighttime or low-irradiance PV data?

- ◯ The sensors stop working at night
- ◯ Power values are dominated by noise
- ◯ The physics model cannot run
- ◯ AI models require daylight

10. Which of the following practices are important for ensuring high-quality photovoltaic (PV) data used in modeling or analysis? (Select all that apply)

- [ ] Removing missing values and physically unrealistic measurements caused by sensor errors
- [ ] Aligning timestamps when combining data from multiple sensors (e.g., PV, weather, irradiance)
- [ ] Filtering out nighttime or very low-irradiance data when analyzing PV performance
- [ ] Checking that measured power values are consistent with voltage and current readings

Section D: Qualitative Understanding of AI's Role

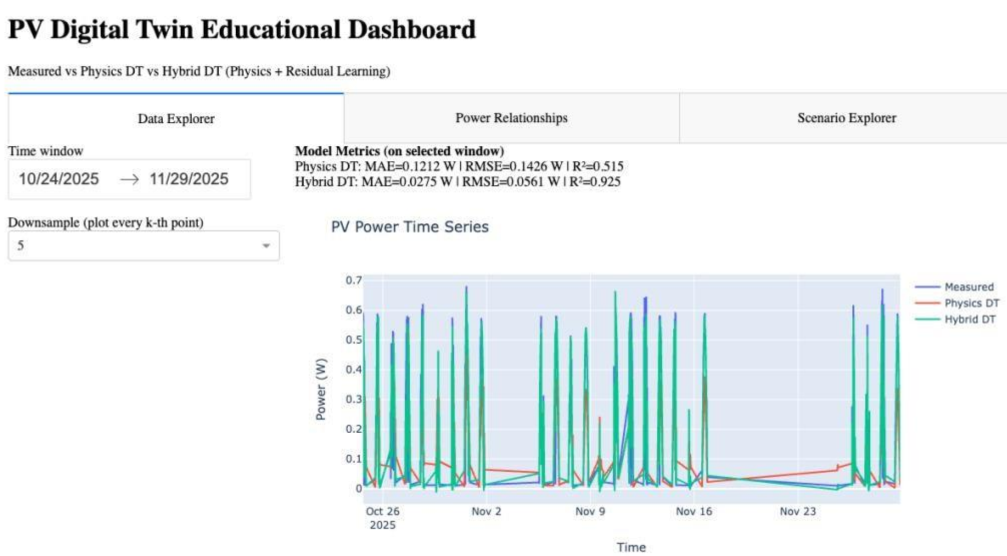
11. In engineering, what is the main role of Artificial Intelligence (AI)?

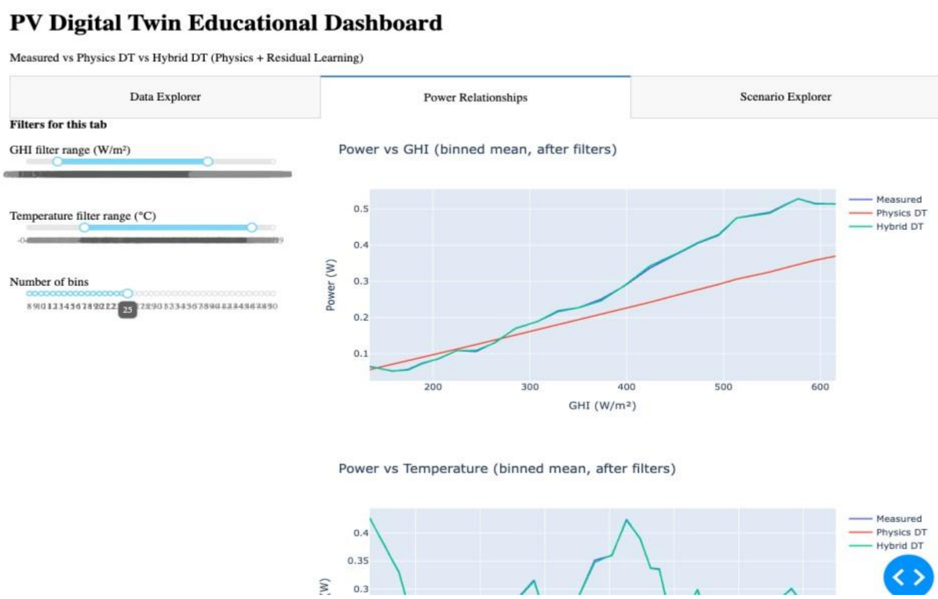
- [ ] Replace physical laws
- [ ] To automatically generate data
- [ ] To identify patterns and relationships from data
- [ ] To eliminate the need for sensors

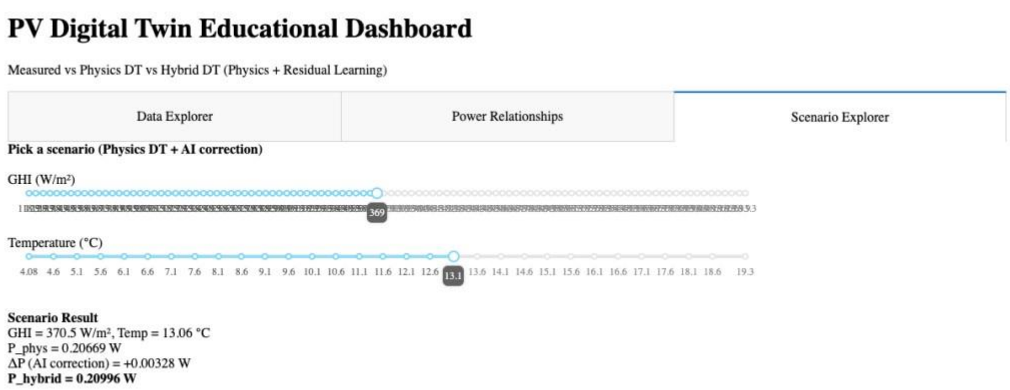
12. Why might engineers combine traditional models with AI-based methods?

- [ ] Traditional models are always incorrect
- [ ] AI is faster than physics in all situations
- [ ] Real-world systems often have complexity, noise, or uncertainty that models alone cannot capture
- [ ] Engineering models are no longer needed

Appendix II – Dashboard Screenshots







Appendix III – Lab Activity Prompts

Solar PV Digital Twin Student Engagement Lab Activity

Hybrid Digital Twins combine physics understanding with data-driven correction to better represent real-world PV behavior. You can add to your lab slide:

"The dashboard is shared via a public link generated by ngrok. Each session produces a temporary URL you can open in your browser. The link works only while the dashboard and ngrok are running."

Lab Purpose

In this lab, you will use an interactive **Digital Twin dashboard** to explore how a solar photovoltaic (PV) system behaves under different environmental conditions. You will compare **measured data**, **physics-based predictions**, and **AI-enhanced (hybrid) predictions**.

Part 1: Data Explorer – Understanding Real PV Data Goal:

Observe how PV power changes over time.

Steps1

1. Open the **Data Explorer** tab.
2. Select a **time window** (e.g., 5 - 7 days).
3. View the **Power Time Series**:
   - Measured Power
   - Physics DT
   - Hybrid DT
4. Adjust the **downsample** option if the plot looks crowded.

Think About

- Which model follows the measured data more closely?
- Why might the physics model differ from measurements?
- What do you observe about PV power output during early morning, late evening, or nighttime hours? Why does this occur?

Part 2: Power Relationships – Cause and Effect

Goal: Understand how the environment affects PV power.

Steps

1. Open the **Power Relationships** tab.
2. View:
   - **Power vs Irradiance**
   - **Power vs Temperature**
3. Compare the three curves:
   - Measured
   - Physics DT
   - Hybrid DT

Think About

- How does power change with sunlight (GHI)?
- How does temperature affect PV power?
- Which model best matches real behavior?

Part 3: Scenario Explorer – "What If?" Analysis Goal:

Build intuition by changing conditions.

Steps

1. Open the **Scenario Explorer** tab.
2. Adjust:
   - **GHI (sunlight) slider**
   - **Temperature slider**

3. Observe:
    - Physics DT prediction
    - AI correction o Final Hybrid DT output

Think About

- What happens when sunlight increases?
- How does temperature change the prediction?
- Why does the AI correction improve the result?

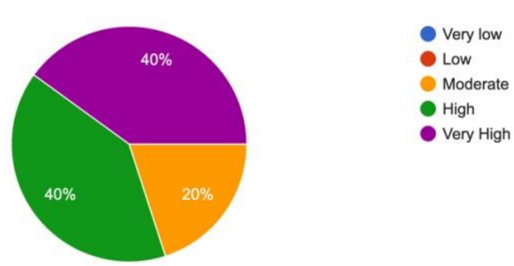
Reflection Questions (Answer Briefly)

1. What did the Digital Twin help you understand that raw data alone could not?
2. Why does the Hybrid DT perform better than the Physics DT?
3. How could this tool help engineers design or operate PV systems?

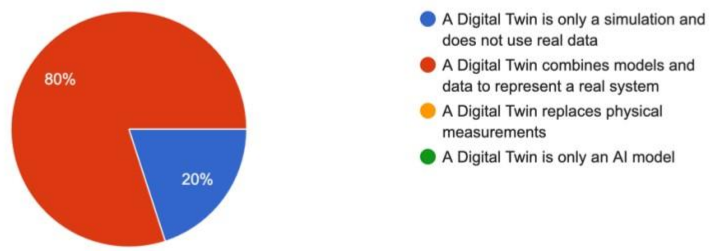
Appendix IV – Post-Lab Learning & Engagement Assessment

Q1. After completing the lab, how would you rate your understanding of how a Digital Twin can be used to study a photovoltaic (PV) system?

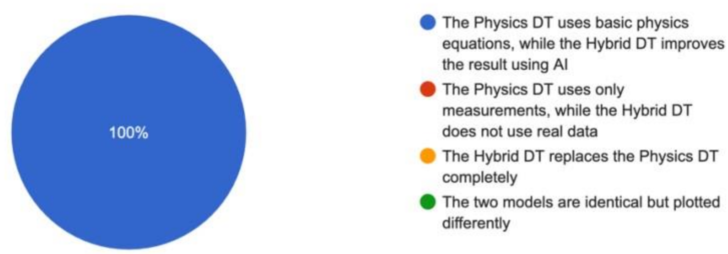
5 responses



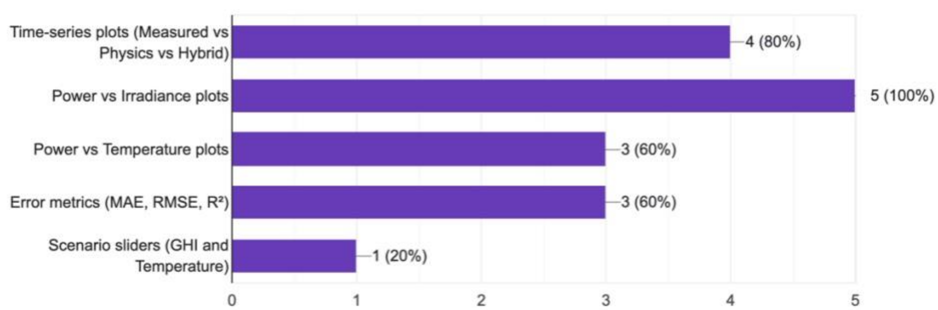
Q2. Which statement best describes your understanding after using the dashboard?
5 responses



Q3. After completing the lab, how would you describe the main difference between the Physics Digital Twin and the Hybrid Digital Twin?
5 responses

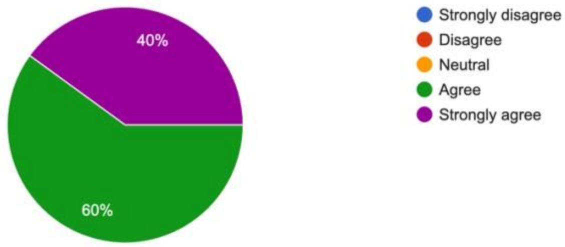


Q4. Which dashboard features helped you most in understanding PV behavior? (Check all that apply)
5 responses



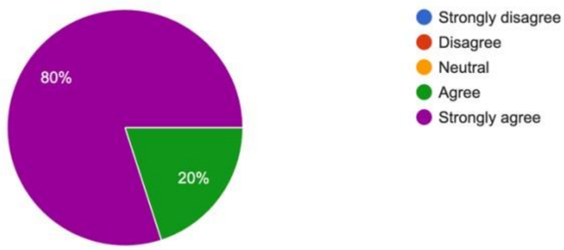
Q5. Adjusting irradiance (GHI) and temperature sliders helped me understand how environmental conditions affect PV power.

5 responses



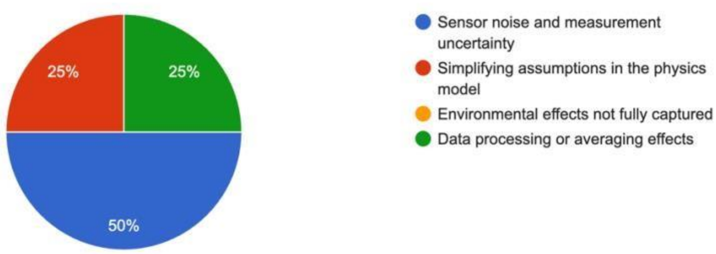
Q6. The time-series plot (Measured vs Physics vs Hybrid) helped me understand when and why model predictions differ from real PV behavior

5 responses



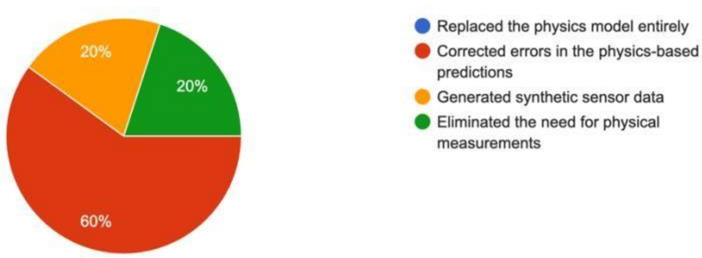
Q7. Why might the physics-based model differ from measured PV power?

4 responses



Q8. What role did the AI (residual model) play in the hybrid Digital Twin?

5 responses



Q9. In one or two sentences, describe **one new concept or insight** you gained from using the Digital Twin dashboard.

5 responses

Solar Irradiance

It is a good platform to help visualize and corroborate this engineering phenomenon.

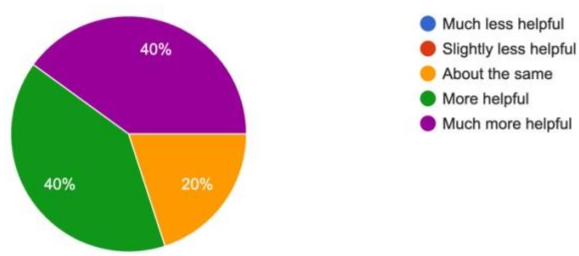
The time plots showing the power during different times in the day helped me understand the two digital twins. Having both the physics and hybrid digital twin being plotted alongside the measured data put into context the performance of each twin

I learned the relationship between photovolactic technologies and electricity (powr, voltage, current)

seeing how the PV is used in the digital twin, and also how there is an effect in the PV with respect to the daytime.

Q10. How helpful was the dashboard in supporting your learning compared to a traditional lecture or static simulation?

5 responses



Q11. What improvements would help you better understand PV systems using this dashboard?

5 responses

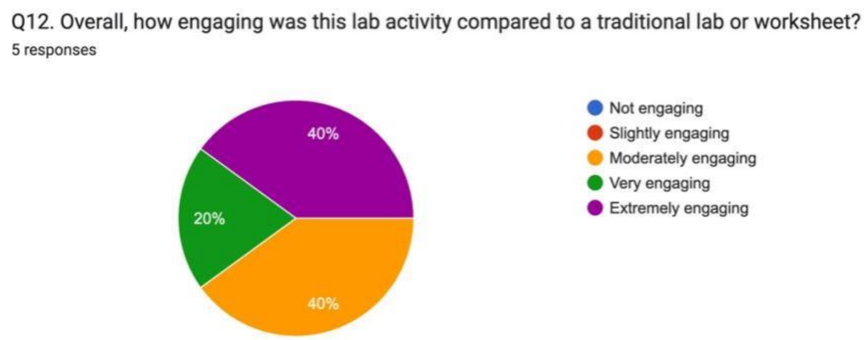
Performing formula based calculations and other means of visualization

Better graphic user interface for high engagement.

I think just having small descriptions for the different explorers might help. Like a little question popup that a user can look at for clarity. I understood a lot of this especially due to my background but for someone who may be new to solar energy they could potentially benefit from the added suggestion.

More graphics

Probably by adding time in the dashboard to show day or night time.



Appendix V – Notation and Symbols

Model Variables

Symbol	**Description**	**Unit**
$P\_meas(t)$	Measured power output at time t	W
$P_{phys}(t)$	Physics-based model predicted power	W
$P_{DT}(t)$	Hybrid model predicted power	W
$\hat{r}_{AI}(t)$	AI residual correction term	W
$G(t),$	Global horizontal irradiance at time t	W/m²
$T(t)$	Cell/ambient temperature at time t	°C
$V(t)$	Measured voltage at time t	V
$I(t)$	Measured current at time t	A

Single-Diode Model Parameters

Symbol	**Description**	**Unit**
I_{ph}	Photocurrent	A
I_0	Diode saturation current	A
R_s	Series resistance	Ω
R_{sh}	Shunt resistance	Ω
a	Diode ideality factor	—

Performance Metrics

Symbol	Description	Formula
MAE	Mean Absolute Error	$(1/n)\ \Sigma$
RMSE	Root Mean Square Error	$\sqrt{[(1/n)\ \Sigma(y\_i - \hat{y}\_i)^2]}$
R^2	Coefficient of Determination	$1 - [\Sigma(y\_i - \hat{y}\_i)^2 / \Sigma(y\_i - \bar{y})^2]$

Key Equations

Measured Power: $P_{meas}(t) = V(t) * I(t)$

Physics-Based Model: $P_{phys}(t) = f_{phys}(G(t), T(t))$

Hybrid Digital Twin: $P_{DT}(t) = P_{phys}(t) + \hat{r}_{AI}(t)$