Type of Contribution:

Research Paper
Review Paper
Case Study

ENERGY: JURNAL ILMIAH ILMU-ILMU TEKNIK
Special Issue 2025 pp 362-370
DOI: 10.51747/energy.si2025.252

E-ISSN: 2962-2565

This article contributes to:

SUSTAINABLE DEVELOPMENT GOALS

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

From THD to Causality: An Epistemology of Artificial-Intelligence–Based Harmonic Analysis in Hybrid Microgrids

Ana Nuril Achadiyah[1]*, Arif Nur Afandi[1], Syaad Patmanthara[1]

[1] Department of Electrical Engineering and Informatics, State University of Malang, 65114, **Indonesia**

*ana.nuril.2505349@students.um.ac.id

Abstract

Rising penetration of photovoltaic generation, wind turbines, battery energy storage systems (BESS), and electric-vehicle charging stations (EVCS) in hybrid microgrids complicates the landscape of harmonics. Practice still relies heavily on FFT-based measurements and THD/TDD indices; however, source attribution and causality are often inconclusive. Epistemic stances shape how we measure, explain, and justify technical claims about harmonics. We propose Epistemically-Informed Harmonic AI (EPI-HAI), which combines standardized measurements (IEC/IEEE), physics-constrained AI modeling (KCL/KVL, impedance), explainable AI (SHAP/Grad-CAM), and uncertainty management to strengthen epistemic trust. The paper clarifies the linkage between epistemology and methodology, formulates physics-informed AI for harmonic analysis, and discusses implications for electrical-engineering curricula.

Keywords: Epistemology; Harmonics; THD/TDD; Hybrid Microgrid

Article Info
Submitted: 2025-10-25
Revised: 2025-12-21
Accepted: 2025-12-25
Published: 2025-12-30

1. Introduction

Integrating energy sources such as photovoltaic (PV) units, wind turbines, battery energy storage systems (BESS), and electric-vehicle charging stations (EVCS) into hybrid microgrids significantly enriches the harmonic and inter harmonic spectra of power networks. These phenomena lead to increased losses, equipment heating, resonance, protection mis operation, and reduced equipment lifetime [4], [5]. Power quality assessments typically stop at Total Harmonic Distortion (THD) or Total Demand Distortion (TDD) thresholds—for example, 5% THD and 5–20% TDD

Publisher
Universitas Panca Marga

as specified in IEEE Std 519-2014 [1]. However, such indices indicate only that power quality is unsatisfactory; they do not identify the underlying causes or sources.

Through the lens of epistemology, this study emphasizes the importance of not just understanding what is being measured (THD/TDD), but also why these measurements matter and how the underlying causes (e.g., electrical laws and network dynamics) influence our measurements. This approach allows us to not only identify power quality issues but also understand the reasons behind the observed phenomena.

Applying artificial intelligence (AI) for source classification and risk prediction raises epistemological questions: when can a prediction be considered valid and trustworthy knowledge. We identify three gaps: (i) an overreliance on THD/TDD metrics that often ignores the causal relations underlying spectral patterns; (ii) black-box AI models that may memorize historical patterns while disregarding electrical laws (e.g., KCL/KVL) and network impedance [12]; and (iii) overlooked instrument and measurement uncertainties that critically affect reliability [6].

To address these issues, we adopt a philosophy-of-science lens to evaluate the validity of technical claims while constructing models that are consistent with electrical mechanisms. In a Popperian view, a technical claim is valid insofar as it is open to testing and falsification [8]. In power-quality studies, statements such as "THD complies with IEEE 519" must be verifiable using standardized measurements. However, as Kuhn reminds us, scientific practice operates within paradigms that shape how problems are perceived [9]. The paradigm that focuses solely on THD is giving way to one that incorporates transparent, auditable, physics-based AI.

Following Bhaskar's critical realism, robust knowledge does not end with surface phenomena (signals and spectra) but bridges to the underlying causal mechanisms [10]. Physics-informed AI for example, PINNs helps ensure that models respect electrical laws [12]. A Bayesian framework then provides the mathematics to manage uncertainty, reporting degrees of belief as probability distributions rather than single values [6]. Finally, causal analysis à la Pearl emphasizes distinguishing correlation from causation through interventions and auxiliary evidence such as operation logs or n-order harmonic patterns [7].

2. Methods

This study maps the relationship between epistemic positions and methodological choices in harmonic analysis—spanning measurement, feature extraction, modeling, and validation. We employ EPI-HAI, an integration of international measurement standards (IEC 61000-4-7, IEC 61000-4-30), physics-constrained AI (KCL/KVL, network impedance), explainable AI (SHAP, Grad-

CAM), and uncertainty management to strengthen epistemic confidence in the results. A PV–BESS–EVCS microgrid vignette illustrates the framework (see **Figure 1.** for the conceptual architecture).

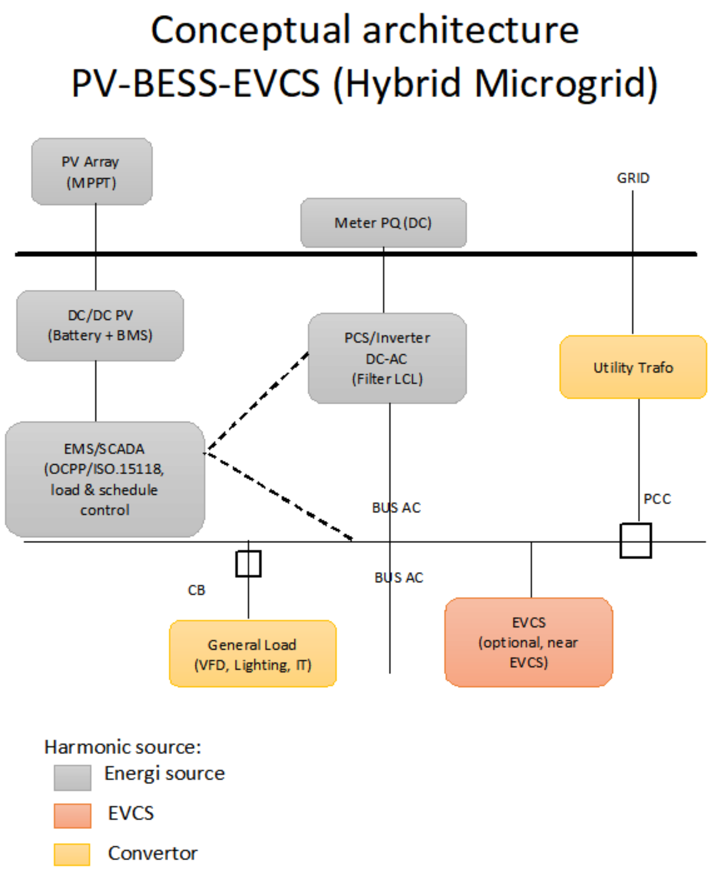

Figure 1. Conceptual Architecture of the PV–BESS–EVCS Hybrid Microgrid

Physics-Informed Neural Networks (PINNs) are employed to ensure that the AI model adheres to fundamental electrical laws, particularly Kirchhoff's Current Law (KCL) and Voltage Law (KVL). These laws are encoded as constraints in the model's architecture, guiding the learning process to produce predictions that are consistent with physical reality. This approach allows the AI model not only to predict harmonic behavior but also to explain the causal relationships behind the observed phenomena.

EPI-HAI ensures that technical results—numerical values, plots, and decisions—are trustworthy because they derive from standardized measurement processes, are explainable, and are grounded in physical causality. Data are acquired with instruments compliant with IEC 61000-4-30 and processed in accordance with IEC 61000-4-7. Signals are transformed into informative representations (FFT, STFT, WPT). AI models for estimation and detection are used to quantify THD/TDD and to recognize source patterns. Predictions must satisfy KCL/KVL and remain consistent with network impedance and topology. Model decisions are explained using SHAP to trace the factors underlying each output. Instrument and model uncertainties are characterized and reported as intervals. AI findings are validated causally by triangulating multi-order harmonic patterns, operation logs, and network parameters. Mitigation recommendations—active/passive filters, capacitor retuning, inverter setpoints, and EVCS scheduling—are justified and benchmarked against IEEE 519 compatibility limits.

2.1 Problem Identification

In a PV–BESS–EVCS hybrid microgrid, increased EV charging between 18:00 and 20:00 resulted in a rise in the current THD at the point of common coupling (PCC) to approximately ±9%. The spectrum exhibited pronounced peaks at the 5th, 7th, and 11th orders characteristic of six-pulse rectifier/converter distortion with minor interharmonic components attributable to PWM modulation [4], [5].

2.2. Design and Conceptual Approach

We adopt a conceptual–analytical approach focused on building the EPI-HAI framework that integrates international metrology standards, physics-based AI, XAI, and Bayesian uncertainty management [1]-[3], [6], [11].

The procedure comprises four stages:

1. A literature review of harmonic standards (IEEE Std 519-2014; IEC 61000-4-30; IEC 61000-4-7) and philosophy-of-science/causality (Popper, Kuhn, Bhaskar, Pearl) [1], [3], [7], [10];
2. A conceptual analysis linking epistemic positions to harmonic methodology—from measurement to spectral processing (FFT/STFT/WPT), AI modeling, and validation [4], [5], [12]; and The development of a PV–BESS–EVCS vignette centered on a THD-I rise and explained via SHAP maps [11], [12].

Formulation of the EPI-HAI Workflow. Based on the integrated conceptual results, we construct eight principal steps, summarized in **Figure 1.** Acquire data using instruments compliant with IEC 61000-4-30 and process measurements in accordance with IEC 61000-4-7; convert signals to spectral representations using FFT, STFT, or WPT [4], [5]; perform detection and estimation with AI models to quantify THD/TDD and recognize harmonic source patterns [4], [5]; impose physics constraints so that predictions remain consistent with KCL/KVL and network impedance/topology [12]; explain model decisions with SHAP and Grad-CAM to identify the harmonic orders or bands that contribute most to the outputs [11]; quantify predictive uncertainty via Bayesian inference or MC-Dropout, reporting credible intervals for the results [6]; and validate AI findings by triangulating multi-order evidence, EVCS operation logs, and network parameters, aligning with Pearl's causal framework and Popper's falsifiability principle [7], [8]. Finally, translate the analysis into mitigation recommendations (e.g., active/passive filters, capacitor retuning, inverter setpoints, EVCS scheduling) and benchmark them against IEEE 519 compatibility limits [1].

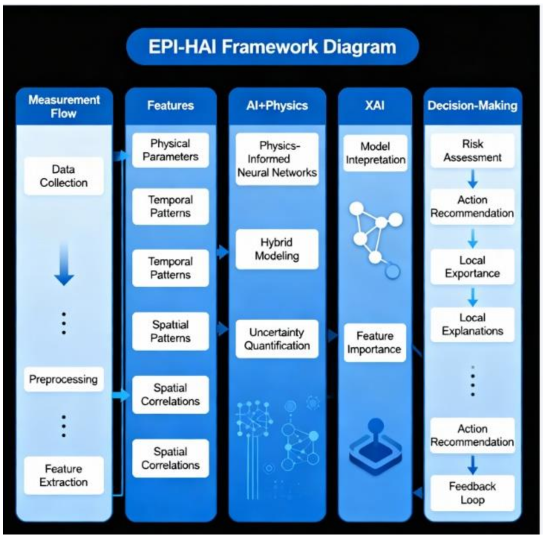

Figure 2. The EPI-HAI Workflow for Harmonic Analysis in Hybrid Microgrids

3.Results and Discussion

3.1 Valid Knowledge in Harmonic Analysis

The findings affirm that predictive accuracy is not synonymous with scientific explanation. In an engineering epistemology, trustworthy knowledge does not end with a model's ability to recognize data correlations; it must also account for the physical mechanisms underlying the phenomenon. For example, an AI model trained solely on historical patterns may predict THD values accurately yet fail to explain why prominent harmonic peaks appear at the 5th, 7th, and 11th orders. Such a model merely describes empirical symptoms (signals, spectra) without reaching the actual causal structure (topology, impedance, converter control modes). By employing Physics-Informed Neural Networks (PINNs), the model is compelled to satisfy electrical laws (KCL/KVL) and system-impedance characteristics, yielding explanations that align with physical reality rather than mere curve fitting.

3.2 AI Integration and Causality

The conceptual experiment on the PV–BESS–EVCS microgrid vignette Figure 3. indicates that the ~9% THD-I peak observed between 18:00 and 20:00 arises from two main factors:

1. Dominance of the 5th, 7th, and 11th harmonic orders due to simultaneous operation of PWM-based converters in the EVCS and the PV inverter; and
2. A possible resonance with the capacitor bank that amplifies specific harmonic amplitudes.

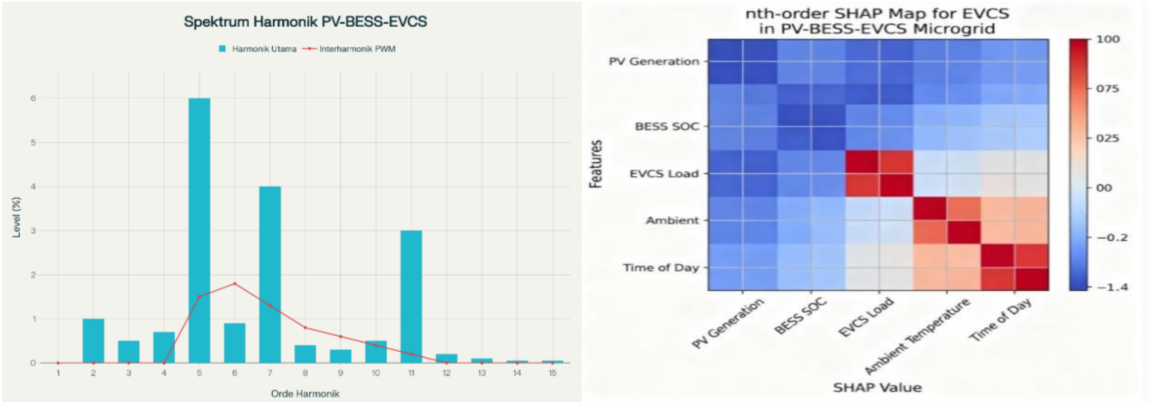

Figure 3. Harmonic Spectrum and SHAP Map

The identified sources of harmonic distortion—specifically, the interaction between the EVCS bus and the capacitor bank—point to potential mitigation strategies. For example, capacitor retuning can address resonance effects by adjusting the system's impedance characteristics, while active/passive filters can be deployed to target specific harmonic orders (e.g., the 5th, 7th, and 11th orders) as predicted by the AI model. These strategies are not only informed by harmonic analysis but are also benchmarked against IEEE 519 standards to ensure compatibility and effectiveness. Using SHAP, we identified that EVCS-related features (e.g., charging frequency, voltage levels) contributed most significantly to the observed THD surge. Meanwhile, Grad-CAM provided a visual representation of which harmonic orders (5th, 7th, and 11th) were most responsible for the distortion at specific times of the day. With this approach, we successfully pinpointed the EVCS bus as the main source of distortion, and the results were consistent with the observed physical phenomena.

The uncertainties in the THD-I prediction are quantified using Bayesian inference, with credible intervals reported as ±0.6%. These intervals represent the model's degree of confidence in its predictions and guide decision-making by indicating the range of possible outcomes. For instance, a THD-I of 8.7% ± 0.6% suggests a high degree of certainty that the distortion will remain within this range, providing stakeholders with valuable information for robust decision-making. The triangulation of multi-order harmonic patterns, EVCS operation logs, and network impedance data strengthens the claim that the primary source of distortion is the interaction between the EVCS and the capacitor bank. The multi-order harmonic patterns provide a spectral fingerprint of the distortion, while the EVCS logs reveal the timing of charging events that correlate with THD peaks. Finally, network impedance data indicate that resonance at certain harmonic orders is exacerbated by the system's configuration. This combined evidence forms a robust causal argument for the source of distortion

3.3 Evidence Triangulation and Epistemic Strengthening

Causal triangulation within the EPI-HAI framework integrates three primary forms of evidence:

1. Multi-order harmonic patterns obtained under IEC 61000-4-7 measurements;
2. EVCS operation logs (switching events) that reveal temporal links between charging periods and harmonic surges; and
3. Network-impedance and capacitor-bank parameters indicating potential local resonance.

The combination of these evidences strengthens the technical claim that the principal source of distortion is not the PCC as a whole but the interaction between the EVCS bus and the capacitor bank, which induces resonance at the 5th–11th harmonic orders. In this triangulated approach, each technical claim is tested against evidence that could falsify or confirm it. In addition, reporting results as confidence (credible) intervals—for example, THD-I = 8.7% ± 0.6%—follows probabilistic machine-learning principles, which require quantitative findings to be accompanied by measures of uncertainty to support unbiased interpretation.

The Explainable AI approach transforms predictions into auditable technical arguments. With SHAP and Grad-CAM, each model decision can be traced back to relevant input features—for instance, the increasing 5th-order harmonic current that tracks higher EVCS charging during peak hours. SHAP thus serves as an epistemic tool that bridges numerical prediction (AI) and technical reasoning (electrical engineering). When combined with physics-informed modelling, the result is not only accurate but also transparent and aligned with underlying physical laws

4. Conclusion

This study affirms that harmonic analysis in hybrid microgrids cannot stop at THD/TDD figures alone; it must be underpinned by physical causality and scientific epistemology so that technical decisions are trustworthy and rationally defensible. Through the development of the EPI-HAI (Epistemically-Informed Harmonic AI) framework, we unify four core pillars:

1. Standardized Measurement.
   Use IEC 61000-4-30 for measurement methods and IEC 61000-4-7 for spectral processing, and benchmark results against IEEE Std 519-2014 compatibility limits to ensure consistency and comparability of measured data.
2. Physics-Constrained AI.
   Constrain AI models with Kirchhoff's laws (KCL/KVL) and system-impedance characteristics—aligned with the concept of Physics-Informed

Neural Networks (PINNs)—so predictions remain faithful to electrical reality.

3. Explainable AI (XAI).
   Apply SHAP (SHapley Additive Explanations) and Grad-CAM to attribute contributions of specific harmonic orders to model outputs, rendering decisions transparent, auditable, and technically accountable.
4. Causal Triangulation and Uncertainty Reporting.
   Combine multi-order harmonic patterns, EVCS operation logs, and network profiles to verify cause–effect relations rather than mere correlations, and report results with uncertainty to support unbiased interpretation.

By integrating these pillars, THD—once merely descriptive—is transformed into epistemic, causal knowledge that explains why a phenomenon occurs, not only that it occurs. Consequently, EPI-HAI is not only a methodological innovation but also a philosophical contribution that strengthens the scientific foundations of AI-enabled power-system analysis, bridging data, physical laws, and testable scientific knowledge.

Acknowledgement

The authors would like to acknowledge the support from the Electrical Engineering Laboratory, Universitas Islam Malang, to run the experiments of the research.

Authors' Declaration

Authors' contributions and responsibilities - The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation, and discussion of results. The authors read and approved the final manuscript.

Funding - No funding information from the authors.

Availability of data and materials - All data is available from the authors.

Competing interests - The authors declare no competing interest.

Additional information - No additional information from the authors.

References

[1] IEEE Standard 519-2014, Recommended Practice and Requirements for Harmonic Control in Electric Power Systems, IEEE, 2014.
[2] IEC 61000-4-30, Testing and Measurement Techniques—Power Quality Measurement Methods, International Electrotechnical Commission, 2015.
[3] IEC 61000-4-7, General Guide on Harmonics and Interharmonics Measurements and Instrumentation, International Electrotechnical

Commission, 2002.
[4] J. Arrillaga and N. R. Watson, Power System Harmonics, 2nd ed. Hoboken, NJ, USA: Wiley, 2003.
[5] M. H. J. Bollen and I. Y. H. Gu, Signal Processing of Power Quality Disturbances. Hoboken, NJ, USA: Wiley-IEEE Press, 2006.
[6] K. P. Murphy, Probabilistic Machine Learning: An Introduction. Cambridge, MA, USA: MIT Press, 2022.
[7] J. Pearl, Causality: Models, Reasoning, and Inference, 2nd ed. Cambridge, U.K.: Cambridge University Press, 2009.
[8] K. Popper, The Logic of Scientific Discovery. London, U.K.: Routledge, 1959.
[9] T. S. Kuhn, The Structure of Scientific Revolutions, 2nd ed. Chicago, IL, USA: University of Chicago Press, 1970.
[10] R. Bhaskar, A Realist Theory of Science. London, U.K.: Routledge, 2008.
[11] S. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," Proc. NeurIPS, 2017.
[12] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks," J. Comput. Phys., 2019.
[13] L. Augusto Horta Nogueira and R. Silva Capaz, "Biofuels in Brazil: Evolution, achievements and perspectives on food security," Global Food Security, vol. 2, no. 2, pp. 117–125, 2013.
[14] A. Pradhan and C. Mbohwa, "Development of biofuels in South Africa: Challenges and opportunities," Renewable and Sustainable Energy Reviews, vol. 39, no. 2014, pp. 1089–1100, 2014.
[15] M. Messagie, K. Lebeau, T. Coosemans, C. Macharis, and J. Van Mierlo, "Environmental and financial evaluation of passenger vehicle technologies in Belgium," Sustainability, vol. 5, no. 12, pp. 5020–5033, 2013.