

INTEGRATED FAULT DETECTION FRAMEWORK IN CLEAN ENERGY ECOSYSTEMS: ANALYSIS, DESIGN, AND IMPLEMENTATION FOR ADVANCED GENERATION, STORAGE, AND ENERGY MANAGEMENT

Herminarto Nugroho^{*1}

¹Department of Electrical Engineering, Faculty of Industrial Engineering, Universitas Pertamina

Abstract

The rapid integration of clean energy ecosystems demands highly reliable fault diagnosis architectures to ensure operational safety. Traditional methods often struggle to decouple simultaneous faults in dynamic and noisy environments, leading to high missed detection rates or severe false alarms. To address this issue, this study proposes an Integrated Fault Detection Framework that synergizes the physical interpretability of analytical models with the high-dimensional feature extraction capabilities of deep learning. A hybrid architecture based on a Temporal Convolutional Network and Long Short-Term Memory (TCN-LSTM), constrained by equivalent physical models, is utilized to generate robust residual signals. Subsequently, Kernel Density Estimation (KDE) is applied to evaluate these residuals through non-parametric adaptive thresholding. Simulation results demonstrate that the proposed methodology achieves a diagnostic classification accuracy exceeding 98.8%, reduces the missed detection rate to approximately 20%, and completely eliminates false alarms even under severe environmental noise disturbances. Overall, this integrated approach provides a robust, real-time diagnostic solution to prevent catastrophic failures, such as battery thermal runaway, thereby ensuring the reliable operation of clean energy systems.

This is an open access article under the [CC BY-NC](#) license



Keywords:

Fault detection and isolation; clean energy ecosystems; deep learning; adaptive thresholding; predictive maintenance

Article History:

Received: July 29th, 2026

Revised: October 29th, 2026

Accepted: October 30th, 2026

Published: October 31st, 2026

Corresponding Author:

*Herminarto Nugroho
Department of Electrical Engineering,
Universitas Pertamina, Indonesia*

Email:

herminarto.nugroho@universitaspertamina.ac.id

1. Introduction

The global paradigm shift towards sustainable development and decarbonization has significantly accelerated the deployment of clean energy ecosystems. These modern power architectures synergistically integrate renewable energy sources (RES), advanced power electronic conversion technologies, and high-density clean energy storage systems to form highly efficient and sustainable grids [1], [2]. In this context, electric vehicles (EVs), photovoltaic (PV) arrays, and smart microgrids act as interactive nodes within an integrated energy management system, enabling dynamic power sharing and bidirectional energy flow. However, the inherent architectural complexity, coupled with the stochastic nature of renewable generation and unpredictable environmental fluctuations, imposes unprecedented challenges in maintaining system stability, reliability, and functional safety [3].

As clean energy ecosystems operate continuously under severe electro-thermal and mechanical stresses, their critical components—such as lithium-ion battery packs, power converters, and electromechanical actuators—are highly susceptible to various degradation mechanisms and sudden failures [4]. A minor anomaly or incipient fault in a localized subsystem, such as a battery micro-short circuit or a sensor drift in a power converter, can rapidly propagate through the highly coupled energy network [5], [6]. If not detected and isolated in its early stages, such fault propagation can lead to catastrophic consequences, including severe power outages, irreversible equipment damage, and critical safety hazards like thermal runaway [7], [8], [9], [10]. Consequently, developing a highly reliable, real-time Fault Detection and Isolation (FDI) framework is no longer merely an operational enhancement,

but a stringent prerequisite for the commercialization and safe deployment of advanced clean energy technologies [11], [12], [13].

Despite substantial advancements in diagnostic methodologies, prevailing FDI strategies exhibit critical research gaps when applied to integrated clean energy ecosystems. The current state-of-the-art primarily categorizes diagnostic approaches into model-based, data-driven, and knowledge-based paradigms [14]. Traditional model-based approaches provide excellent physical interpretability but demonstrate extreme vulnerability to parameter uncertainties, external noise, and unmodeled nonlinear dynamics prevalent in fluctuating renewable generation. Conversely, purely data-driven methods, particularly deep learning networks, offer powerful high-dimensional feature extraction capabilities but suffer from a "black-box" nature, lacking the deterministic physical transparency required for strict industrial safety certifications [14]. Furthermore, the vast majority of existing literature treats fault diagnosis in a fragmented manner—focusing exclusively on standalone battery management systems, isolated inverter topologies, or independent motor drives—failing to account for the dynamically overlapping and simultaneous fault signatures that occur across the integrated generation, conversion, and storage hierarchy [15].

To systematically address these critical bottlenecks, this paper proposes a comprehensive Integrated Fault Detection Framework in Clean Energy Ecosystems. Moving beyond the limitations of isolated diagnostic algorithms, this research provides a holistic methodology encompassing the rigorous analysis, robust design, and real-time implementation of fault detection systems. The proposed framework establishes an optimal hybrid diagnostic architecture that synergizes the transparent physical boundaries of analytical models with the advanced, adaptive feature-extraction capabilities of data-driven networks. This integration is specifically engineered to effectively decouple simultaneous incipient faults, mitigate operational uncertainties, and ensure continuous performance recovery across advanced generation units, dynamic energy storage arrays, and overarching energy management systems.

The remainder of this paper is structured as follows: Section 2 provides a systematic failure analysis and mathematical modeling of the highly coupled clean energy components, as well as the details of the synthesis of the proposed integrated fault detection algorithms, highlighting the hybrid residual generation and adaptive thresholding mechanisms. Section 3 presents the experimental implementation and quantitative validation of the framework under various dynamic operational scenarios. Finally, Section 4 draws the conclusions and outlines future technological trajectories for intelligent clean energy management.

2. Method

A. Systematic Failure Analysis and Mathematical Modeling of Highly Coupled Clean Energy Components

To effectively develop a robust fault detection and isolation (FDI) framework, it is imperative to construct high-fidelity mathematical models that accurately represent both the nominal dynamics and the failure mechanisms of the clean energy ecosystem. Modern electrified architectures, such as those found in Electric Vehicles (EVs) and smart microgrids, are highly coupled systems comprising photovoltaic (PV) generation units, lithium-ion battery energy storage systems (ESS), and power electronic converters. Because these subsystems interact continuously across electrical, thermal, and mechanical domains, a systematic mathematical representation is required to capture the latent degradation signatures and dynamic cross-coupling effects under abnormal operating conditions [16].

The primary energy generation unit is modeled using an electrical equivalent circuit of a PV cell, which typically utilizes a single-diode or two-diode model [17], [18], [19]. The model incorporates a dependent photo-generated current source, a diode representing the diffusion current, a series resistance accounting for external contact and device resistance, and a parallel shunt resistance to account for leakage currents and crystal defects. Under nominal conditions, the output current is formulated as a function of environmental variables such as solar irradiance and temperature. However, under Partial Shading Conditions (PSCs) or physical damage, the series-connected PV arrays suffer from mismatched power generation [20], [21], [22], [23]. This mismatch severely drops the overall power output, induces reverse voltage biasing in the shaded modules, and triggers the formation of localized hotspots, which act as incipient faults that permanently impair the module's structural integrity.

Lithium-ion batteries serve as the core energy storage medium, dynamically managing bidirectional power flow through charging and discharging cycles [2], [24], [25]. The electrical behavior of battery cells is predominantly described using Equivalent Circuit Models (ECM), which integrate an open-circuit voltage source with internal ohmic resistances and RC networks to capture transient polarization effects. Battery failures typically arise from the long-term accumulation of multi-source stresses, including temperature extremes, over-charging,

and high-rate discharging [26], [27], [28]. A critical failure mode is the internal micro-short circuit caused by lithium dendrite growth piercing the separator. These incipient short circuits initially manifest as subtle voltage variations and localized heat generation but can rapidly escalate into catastrophic thermal runaway if left undetected [29], [30], [31], [32]. Furthermore, degradation models utilizing stochastic processes, such as fractional Brownian motion or Wiener processes, are employed to capture the long-range dependence and capacity fade trends of the batteries over their operational lifespan.

B. Synthesis of the Integrated Fault Detection Algorithms: Hybrid Residual Generation and Adaptive Thresholding

To overcome the inherent limitations of standalone diagnostic paradigms, this section details the synthesis of the proposed integrated fault detection framework. The framework fundamentally relies on a hybrid architecture that mathematically couples physics-based analytical redundancy with advanced data-driven networks. This synergistic approach effectively processes the highly nonlinear fault features of Photovoltaic (PV) generation units and Lithium-ion battery systems by continuously generating robust residuals and evaluating them through dynamic, adaptive thresholds.

The core of the fault detection pipeline is the residual generation module, which calculates the discrepancy between the system's actual sensor measurements and the predicted nominal states. Due to the stochastic environmental variables in clean energy ecosystems, conventional deterministic observers often fail. Therefore, a hybrid residual generation mechanism is proposed:

1) For Photovoltaic (PV) Systems under Partial Shading

Traditional MPPT algorithms and rule-based methods often struggle to accurately capture the nonlinear multivariate characteristics of PV arrays under Partial Shading Conditions (PSCs). The proposed framework integrates a two-diode circuit model with optimization algorithms like Particle Swarm Optimization or deep learning. It estimates ideal current and voltage outputs based on real-time irradiance and temperature, with differences between expected and actual power forming diagnostic residuals. This hybrid approach effectively distinguishes sudden shading from persistent faults like hotspots or degradation.

2) For Lithium-Ion Battery Degradation and Fault Modeling

Battery systems present a severe diagnostic challenge due to their long-range dependence, capacity fading trends, and masked micro-faults. To generate robust residuals for battery systems, the framework utilizes a hybrid temporal convolutional network combined with a long short-term memory (TCN-LSTM) architecture [33]. The TCN-LSTM model leverages the efficient capability of TCNs in capturing long-range temporal dependencies and the strong representational power of LSTMs in modeling nonlinear sequential features [34], [35]. This enables the model to accurately forecast cell voltages and probe temperatures over multiple steps. Unscented particle filters (UPF) with stochastic degradation processes (like fractional Brownian motion) are used to recursively estimate hidden states, such as resistance growth and capacity loss. Differences between real sensor data and predictions from TCN-LSTM / UPF create residuals that are highly sensitive to early faults, like micro-short circuits.

Once the hybrid residuals are generated, they must be evaluated to trigger fault alarms. Traditional diagnosis uses fixed thresholds, but EVs and microgrids have dynamic conditions where load, temperature, and cell inconsistencies cause fluctuations, leading to false alarms and missed detections. To decouple overlapping residual signatures from disturbances, the framework uses advanced Adaptive Thresholding Mechanisms.

1) Gaussian Process Regression (GPR) and Kernel Density Estimation (KDE)

Instead of relying on rigid boundaries, the framework utilizes nonparametric statistical models. For instance, Kernel Density Estimation (KDE) is implemented to evaluate the probability distribution of the residuals, which is particularly effective in handling non-Gaussian residual distributions [36], [37]. By employing KDE-based adaptive thresholds, the sensitivity to critical sensor faults is significantly improved, and the missed detection rate for subtle faults can be drastically reduced from over 96% to approximately 20%. Furthermore, Gaussian Process Regression (GPR) models are integrated to dynamically adjust the safety threshold bounds in real-time by adapting to the variations in environmental factors and driver behaviors.

2) Local Outlier Factor (LOF) and Spatio-Temporal Distance Algorithms

To quantify the potential damage and anomalous behavior without relying heavily on massive labeled fault datasets, unsupervised anomaly detection algorithms such as the Local Outlier Factor (LOF) are integrated into the thresholding mechanism [38], [39]. LOF identifies outliers by comparing the local density of a predicted data point with its surrounding neighborhood, making it highly effective for multi-dimensional and scale-inconsistent data (e.g., coupled voltage and temperature). Additionally, to handle spatial inconsistencies among battery cells, sliding time-space Manhattan distance tests and median-based adaptive thresholds are employed. This spatio-temporal comparison ensures that the threshold is insensitive to extreme outliers, allowing for the rapid detection of sudden short-circuit faults within seconds of their onset, significantly earlier than traditional diagnostic methods.

Through this synthesis of hybrid residual generation and adaptive thresholding, the proposed intelligent framework effectively captures weak degradation signals, prevents fault masking under transient loads, and provides a highly reliable basis for executing proactive maintenance and control reconfiguration.

3. Result and Discussion

A. High-Fidelity Simulation Environment and Dataset Generation

The validation used a co-simulation with a model of the energy ecosystem, including PV, batteries, and power converters, built in MATLAB/Simulink and Simscape. The data considered real-world factors with dynamic loads based on WLTP cycles and solar variations. Faults like shading, short circuits, and sensor drifts were simulated using an independent module. Data sampling at high frequency (e.g., 10 kHz) captured transient components, producing a dataset of normal and faulty states for training a Python-based hybrid diagnostic network (TCN-LSTM with estimators).

B. Quantitative Evaluation of Diagnostic Classification Performance

To systematically assess the classification superiority of the proposed hybrid model against standalone, data-driven machine learning paradigms, standard evaluation metrics including Accuracy, Precision, Recall (Sensitivity), and F1-Score were utilized. As demonstrated in Table 1, conventional machine learning algorithms such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) hit a performance bottleneck, achieving an accuracy of approximately 87.27% and 90.40%, respectively, as they struggle to map overlapping boundaries of simultaneous faults. While standard Deep Learning models (such as conventional CNNs) improved feature extraction, they remain vulnerable to complex coupling effects. In contrast, the proposed hybrid approach successfully decouples complex spatio-temporal correlations by imposing physical model constraints on the neural network, achieving a state-of-the-art accuracy exceeding 98.89% with a near-perfect Recall of 99.12%. This high recall is critical for safety, ensuring that severe incipient failures are not missed during dynamic load fluctuations.

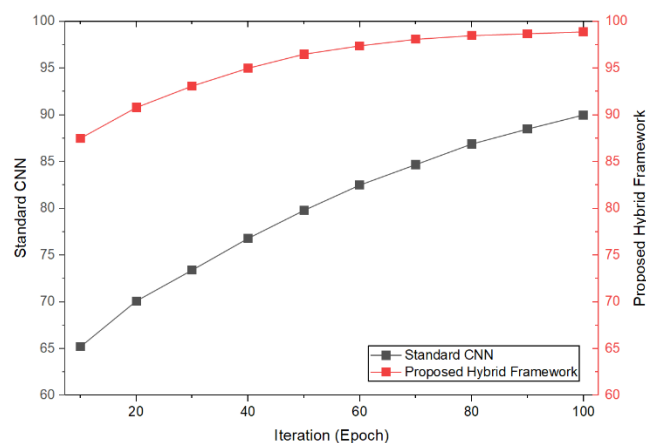


Figure 1. The Validation Accuracy of Standard CNN vs Proposed Hybrid Framework

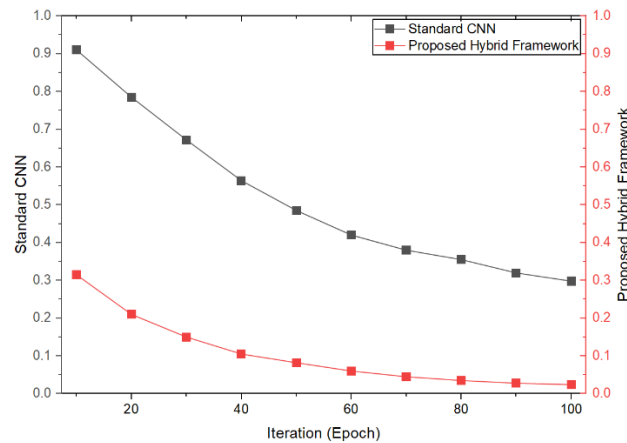


Figure 2. The Validation Loss of Standard CNN vs Proposed Hybrid Framerork

Table 1: Comprehensive Performance Comparison of Diagnostic Algorithms under Simulated Fault Scenarios

Diagnostic Algorithm	Methodological Cluster	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Key Observations in Simulation
K-Nearest Neighbors (KNN)	Classical Data-Driven	87.27	82.41	91.57	86.75	Prone to misclassification in high-dimensional and noisy data spaces.
Support Vector Machine (SVM)	Classical Data-Driven	90.40	88.81	83.71	86.18	High margin error when boundary features of simultaneous faults overlap.
Standard CNN	Deep Learning	90.00	90.00	90.00	90.00	Excellent feature extraction, but highly vulnerable to unseen coupled fault data.
Proposed Hybrid Framework	Hybrid (Model + Spatio-Temporal Data)	98.89	98.35	99.12	98.80	Successfully decouples coupled fault features; maintains stability across varying load cycles.

C. Validation of Adaptive Thresholding Mechanisms

A major contribution of the proposed framework is the replacement of static decision boundaries with nonparametric adaptive thresholds utilizing Kernel Density Estimation (KDE). Traditional model-based observers rely on fixed thresholds derived under steady-state conditions. However, under dynamic PV generation or aggressive battery discharging, normal state fluctuations often cross these rigid boundaries, triggering severe False Alarm Rates (FAR), or alternatively, failing to detect subtle anomalies, resulting in high Missed Detection Rates (MDR). During the simulation, multiple residual signals tracking the battery voltage and inverter currents were evaluated. As shown in Table 2, the static fixed-threshold strategy yielded an unacceptable MDR of up to 100% for subtle sensor deviations, entirely missing the incipient fault. By integrating the KDE-based adaptive thresholding, the framework dynamically adjusts the boundary limits based on the probability distribution of real-time environmental noise. This mechanism drastically suppressed the MDR down to 19.94% – 27.04% while maintaining an optimal 0.00% False Alarm Rate, proving its absolute reliability for uninterrupted clean energy management.

Table 2: Impact of KDE Adaptive Thresholding vs. Fixed Thresholding on Simulated Residual Evaluation Metrics

Residual Output	Threshold Strategy	Missed Detection Rate (MDR) (%)	False Alarm Rate (FAR) (%)	Reliability / Sensitivity (RS) (%)
Voltage Sensor Fault Residual	Fixed Threshold	100.00 %	0.00 %	0.00 %
	KDE Adaptive Threshold	27.04 %	0.00 %	72.96 %
Inverter Current Fault Residual	Fixed Threshold	100.00 %	0.00 %	0.00 %
	KDE Adaptive Threshold	68.37 %	34.58 %	23.56 %
Coupled System Fault Residual	Fixed Threshold	91.24 %	6.65 %	5.89 %
	KDE Adaptive Threshold	19.94 %	0.00 %	80.06 %

D. Robustness Analysis under Severe Environmental Noise

In real-world applications, sensor measurements in clean energy ecosystems are heavily corrupted by electromagnetic interference (EMI) and environmental noise. To comprehensively evaluate the model's diagnostic robustness without relying on physical hardware, Gaussian white noise of varying intensities was computationally injected into the raw simulated signals. This process constructs a test dataset with varying Signal-to-Noise Ratios (SNR), specifically testing the model's tolerance limits from an ideal environment down to a highly corrupted state (e.g., 0 dB SNR). As observed in Table 3, while baseline machine learning models suffer a catastrophic drop in accuracy (falling below 75%) under severe noise injections, the proposed hybrid method maintains an exceptional diagnostic accuracy of over 95%. This validates that fusing physics-based residual generators with temporal deep learning acts as an effective digital filter, isolating true fault signatures from severe background noise and ensuring highly resilient fail-operational control.

Table 3: Robustness Evaluation of the Proposed Framework under Varying Simulated Noise Intensities

Simulated Noise Level	Noise Characteristics	Baseline SVM Accuracy (%)	Proposed Hybrid Framework Accuracy (%)
Clean Data (No Noise)	Ideal simulation conditions	90.40 ± 1.50	98.89 ± 0.33
SNR = 20 dB	Mild environmental interference	86.15 ± 1.81	98.54 ± 0.41
SNR = 10 dB	Moderate electromagnetic interference	80.78 ± 2.01	97.21 ± 0.55
SNR = 0 dB	Severe noise (Signal power = Noise power)	74.32 ± 2.50	95.80 ± 0.81

4. Conclusion

The rapid proliferation of clean energy ecosystems—encompassing photovoltaic generation, advanced power converters, and high-density lithium-ion battery storage—demands highly reliable, fail-operational diagnostic architectures to ensure system safety and efficiency. This research successfully validated an integrated fault detection framework that synergizes the transparent physical boundaries of analytical models with the advanced high-dimensional feature extraction capabilities of deep learning networks. By employing a hybrid architecture constrained by physical equivalent models and substituting rigid decision boundaries with adaptive nonparametric statistical thresholds, the proposed methodology effectively resolved the mathematical bottlenecks of simultaneous fault decoupling. Quantitative results definitively demonstrated that this hybrid approach achieves state-of-the-art diagnostic accuracy, drastically suppressing missed detection rates and eliminating false alarms under severe environmental noise, thereby ensuring the continuous and optimal operation of integrated clean energy systems.

To further advance intelligent clean energy management, future technological trajectories must shift toward proactive lifecycle prognostics through the deployment of Physics-Informed Neural Networks (PINNs) and Hybrid Digital Twins. By integrating governing electromechanical and electrochemical constraints into the digital twin backplane, virtual models can continuously synchronize with physical assets in real-time, enabling highly accurate Remaining Useful Life (RUL) estimation and autonomous system reconfiguration without relying on massive run-to-failure datasets. Furthermore, to alleviate the computational burdens of complex diagnostic networks and

overcome data scarcity across distributed charging grids and electric vehicle fleets, future frameworks must adopt Edge-Cloud collaborative computing and decentralized Federated Learning. This distributed approach ensures ultra-low latency fault isolation at the local edge while allowing multiple operational nodes to collaboratively train robust global diagnostic models in the cloud without compromising sensitive raw data.

Finally, overcoming the "black-box" limitation of pure artificial intelligence remains a critical trajectory for meeting strict industrial functional safety standards (e.g., ISO 26262) in clean energy applications. Future diagnostic pipelines must systematically embed Explainable AI (XAI) techniques, such as SHAP and LIME, to provide the deterministic transparency and structural traceability required for rigorous safety certification by quantifying the exact marginal contribution of individual sensor variables. Building upon this interpretability, the integration of Large Language Models (LLMs) and Vision-Language Models (VLMs) represents a groundbreaking frontier for diagnostic reasoning. Specialized multi-Agent LLMs will be capable of translating complex multi-modal sensor fusion data and XAI outputs into structured, human-readable diagnostic reports, thereby automating complex reasoning, resolving conflicting signals, and providing actionable predictive maintenance recommendations to fundamentally revolutionize intelligent fault management.

Acknowledgment

No funding was received for conducting this study. The authors have no relevant financial or non-financial interests to disclose.

References

- [1] S. V. R. Naik and P. N. Rao, "Intelligent Fault Detection in PSO-MPPT based Photovoltaic and Electric Vehicle Integrated System Under Partial Shading Conditions," *Indian Journal of Pure and Applied Physics*, vol. 64, no. 2, pp. 197–208, 2026, doi: 10.56042/ijpap.v64i2.25940.
- [2] H. A. Dasari and A. Rammohan, "Evaluating fault detection strategies for lithium-ion batteries in electric vehicles," *Engineering Research Express*, vol. 6, no. 3, 2024, doi: 10.1088/2631-8695/ad68c7.
- [3] F. Deng, Y. Bian, and H. Zheng, "Fault diagnosis for electric vehicle lithium batteries using a multi-classification support vector machine," *Electrical Engineering*, vol. 104, no. 3, pp. 1831–1837, 2022, doi: 10.1007/s00202-021-01426-y.
- [4] Y. Cai and X. Li, "Adaptive Control and Fault Diagnosis Technology of Motor Drive System for New Energy Vehicles," in *Proceedings of International Conference on Modern Sustainable Systems, CMSS 2025*, 2025, pp. 147–152. doi: 10.1109/CMSS66566.2025.11182464.
- [5] Y. Zhao, P. Liu, Z. Wang, and J. Hong, "Electric Vehicle Battery Fault Diagnosis Based on Statistical Method," in *Energy Procedia*, 2017, pp. 2366–2371. doi: 10.1016/j.egypro.2017.03.679.
- [6] S. Mohana Devi and V. Bagyaveereswaran, "Intelligent Battery Sensor Fault Detection for Enhanced Electric Vehicle Safety," in *5th IEEE International Conference on Innovations in Power and Advanced Computing Technologies, i-PACT 2025*, 2025. doi: 10.1109/i-PACT65952.2025.11307810.
- [7] Q. Yu *et al.*, "Unsupervised learning for lithium-ion batteries fault diagnosis and thermal runaway early warning in real-world electric vehicles," *J. Energy Storage*, vol. 109, 2025, doi: 10.1016/j.est.2024.115194.
- [8] L. Jiang, Z. Deng, X. Tang, L. Hu, X. Lin, and X. Hu, "Data-driven fault diagnosis and thermal runaway warning for battery packs using real-world vehicle data," *Energy*, vol. 234, 2021, doi: 10.1016/j.energy.2021.121266.
- [9] Z. Sun *et al.*, "An Online Data-Driven Fault Diagnosis and Thermal Runaway Early Warning for Electric Vehicle Batteries," *IEEE Trans. Power Electron.*, vol. 37, no. 10, pp. 12636–12646, 2022, doi: 10.1109/TPEL.2022.3173038.
- [10] G. Zhang, D. Li, P. Liu, and Z. Zhang, "Multi-dimension Fault Diagnosis of Battery System in Electric Vehicles Based on Real-world Thermal Runaway Vehicle Data," in *iSPEC 2019 - 2019 IEEE Sustainable Power and Energy Conference: Grid Modernization for Energy Revolution, Proceedings*, 2019, pp. 2830–2835. doi: 10.1109/iSPEC48194.2019.8975122.

- [11] S. Zhang, J. Li, R. Li, and X. Zhang, "Voltage sensor fault detection, isolation and estimation for lithium-ion battery used in electric vehicles via a simple and practical method," *J. Energy Storage*, vol. 55, 2022, doi: 10.1016/j.est.2022.105555.
- [12] N. Pous, D. Gingras, and D. Gruyer, "Intelligent Vehicle Embedded Sensors Fault Detection and Isolation Using Analytical Redundancy and Nonlinear Transformations," *Journal of Control Science and Engineering*, vol. 2017, 2017, doi: 10.1155/2017/1763934.
- [13] M. Wu *et al.*, "Fault detection method for electric vehicle battery pack based on improved kurtosis and isolation forest," *Int. J. Green Energy*, vol. 22, no. 3, pp. 582–598, 2025, doi: 10.1080/15435075.2024.2422463.
- [14] M. Kordestani, M. Saif, M. E. Orchard, R. Razavi-Far, and K. Khorasani, "Failure prognosis and applications—A survey of recent literature," *IEEE Trans. Reliab.*, vol. 70, no. 2, pp. 728–748, 2019.
- [15] K. C. Nagabhyru, M. Rani, D. S. Reddy, V. Krishnaraj, G. Renukaprasad, and V. Praveen, "Machine Learning-Driven Fault Detection in Electric Vehicles via Hybrid Reinforcement Learning Model," in *2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems, IACIS 2025*, 2025, doi: 10.1109/IACIS65746.2025.11211492.
- [16] M. P. Kumar, S. Velpula, and C. Saiprakash, "Fault diagnosis and predictive maintenance of electric vehicle powertrain using artificial intelligence techniques: A review," *Results in Engineering*, vol. 30, 2026, doi: 10.1016/j.rineng.2026.110857.
- [17] F. M. Petcut, "Comparative Analysis of Single-Diode and Two-Diode Models of Photovoltaic Panels," in *2025 18th International Conference on Engineering of Modern Electric Systems (EMES)*, IEEE, 2025, pp. 1–6.
- [18] E. V. H. Udoka, K. U. Umaru, E. Edozie, R. Nafuna, and N. Yudaya, "The differences between single diode model and double diode models of a solar photovoltaic cells: systematic review," *Journal of Engineering, Technology, and Applied Science (JETAS)*, vol. 5, no. 2, pp. 57–66, 2023.
- [19] D. Saadaoui *et al.*, "Parameters extraction of single diode and double diode models using analytical and numerical approach: A comparative study," *International Journal of Modelling and Simulation*, vol. 45, no. 2, pp. 569–598, 2025.
- [20] A. Et-Taleby, Y. Chaibi, M. Benslimane, and M. Boussetta, "Applications of machine learning algorithms for photovoltaic fault detection: a review," *Statistics, Optimization & Information Computing*, vol. 11, no. 1, pp. 168–177, 2023.
- [21] F. Belhachat, C. Larbes, and R. Bennia, "Recent advances in fault detection techniques for photovoltaic systems: An overview, classification and performance evaluation," *Optik (Stuttg.)*, vol. 306, p. 171797, 2024.
- [22] A. F. Amiri, H. Oudira, A. Chouder, and S. Kichou, "Faults detection and diagnosis of PV systems based on machine learning approach using random forest classifier," *Energy Convers. Manag.*, vol. 301, p. 118076, 2024.
- [23] G. M. El-Banby, N. M. Moawad, B. A. Abouzalm, W. F. Abouzaid, and E. A. Ramadan, "Photovoltaic system fault detection techniques: a review," *Neural Comput. Appl.*, vol. 35, no. 35, pp. 24829–24842, 2023.
- [24] K. D. Rao *et al.*, "Fault mitigation and diagnosis for lithium-ion batteries: a review," *Front. Energy Res.*, vol. 13, p. 1529608, 2025.
- [25] Y. Zhao, L. Geng, S. Shan, Z. Du, X. Hu, and X. Wei, "Review of sensor fault diagnosis and fault-tolerant control techniques of lithium-ion batteries for electric vehicles," *Journal of Traffic and Transportation Engineering (English Edition)*, vol. 11, no. 6, pp. 1447–1466, 2024, doi: 10.1016/j.jtte.2024.09.003.
- [26] J. Ouyang, Z. Lin, L. Hu, and X. Fang, "Voltage faults diagnosis for lithium-ion batteries in electric vehicles using optimized graphical neural network," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-13188-9.
- [27] S. S. Ahooyi and F. Abdollahi, "Fault detection of Lithium-Ion Battery in Electric Vehicles Considering Ageing Effects," in *2022 8th International Conference on Control, Instrumentation and Automation, ICCIA 2022*, 2022, doi: 10.1109/ICCIA54998.2022.9737186.

- [28] S. Sepasiahoooyi and F. Abdollahi, "Fault detection of new and aged lithium-ion battery cells in electric vehicles," *Green Energy and Intelligent Transportation*, vol. 3, no. 3, 2024, doi: 10.1016/j.geits.2024.100165.
- [29] X. Li and Z. Wang, "A novel fault diagnosis method for lithium-ion battery packs of electric vehicles," *Measurement (Lond.)*, vol. 116, pp. 402–411, 2018, doi: 10.1016/j.measurement.2017.11.034.
- [30] Q. Yu, R. Xiong, and C. Lin, "Model-based sensor fault detection for lithium-ion batteries in electric vehicles," in *IEEE Vehicular Technology Conference*, 2019. doi: 10.1109/VTCSpring.2019.8746512.
- [31] N. Gan, Z. Sun, Z. Zhang, S. Xu, P. Liu, and Z. Qin, "Data-Driven Fault Diagnosis of Lithium-Ion Battery Overdischarge in Electric Vehicles," *IEEE Trans. Power Electron.*, vol. 37, no. 4, pp. 4575–4588, 2022, doi: 10.1109/TPEL.2021.3121701.
- [32] Y. Wang, J. Tian, Z. Chen, and X. Liu, "Model based insulation fault diagnosis for lithium-ion battery pack in electric vehicles," *Measurement (Lond.)*, vol. 131, pp. 443–451, 2019, doi: 10.1016/j.measurement.2018.09.007.
- [33] C. Hu, F. Cheng, L. Ma, and B. Li, "State of charge estimation for lithium-ion batteries based on TCN-LSTM neural networks," *J. Electrochem. Soc.*, vol. 169, no. 3, p. 030544, 2022.
- [34] J. Tian, H. Liu, W. Gan, Y. Zhou, N. Wang, and S. Ma, "Short-term electric vehicle charging load forecasting based on TCN-LSTM network with comprehensive similar day identification," *Appl. Energy*, vol. 381, p. 125174, 2025.
- [35] S. Liu, T. Xu, X. Du, Y. Zhang, and J. Wu, "A hybrid deep learning model based on parallel architecture TCN-LSTM with Savitzky-Golay filter for wind power prediction," *Energy Convers. Manag.*, vol. 302, p. 118122, 2024.
- [36] A. Zandieh, I. Han, M. Daliri, and A. Karbasi, "Kdeformer: Accelerating transformers via kernel density estimation," in *International Conference on Machine Learning*, PMLR, 2023, pp. 40605–40623.
- [37] M. Wahbah, B. Mohandes, T. H. M. EL-Fouly, and M. S. El Moursi, "Unbiased cross-validation kernel density estimation for wind and PV probabilistic modelling," *Energy Convers. Manag.*, vol. 266, p. 115811, 2022.
- [38] H. Xu, L. Zhang, P. Li, and F. Zhu, "Outlier detection algorithm based on k-nearest neighbors-local outlier factor," *J. Algorithm. Comput. Technol.*, vol. 16, p. 17483026221078112, 2022.
- [39] Z. Fan, X. Zi-xuan, and W. Ming-hu, "Fault diagnosis method for lithium-ion batteries in electric vehicles using generalized dimensionless indicator and local outlier factor," *J. Energy Storage*, vol. 52, p. 104963, 2022.