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Resilient power system design integrating solar inverters storage and grid interfacing for energy insecure environments

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Abstract

The design of resilient power systems has become a central priority as energy insecurity, climate variability, and infrastructure-fragility continue to challenge electricity provision in many regions of the world. Conventional centralized grids often struggle to deliver reliable power in environments characterized by weak networks, limited redundancy, and exposure to environmental and socio-economic disruptions. In response, distributed renewable energy architectures have emerged as a viable pathway for improving system robustness, access, and adaptability. Solar photovoltaics, when combined with advanced power electronics and storage technologies, offer modular and scalable solutions that can be tailored to local demand and resource availability. This study examines resilient power system design through the integrated deployment of solar inverters, energy storage systems, and grid-interfacing mechanisms, with particular emphasis on energy-insecure environments. From a system-level perspective, the paper explores how inverter-based resources reshape voltage regulation, frequency support, and power quality management in low-inertia networks. The role of energy storage in mitigating intermittency, enhancing ride-through capability, and supporting peak demand is analyzed as a critical enabler of operational resilience. Grid-interfacing strategies, including microgrid configurations and hybrid grid-connected modes, are discussed as mechanisms for balancing autonomy with coordinated operation. Narrowing the focus, the study highlights design considerations for environments with constrained infrastructure, where resilience must account for technical, operational, and contextual limitations. It emphasizes the importance of coordinated control between inverters and storage, adaptive protection schemes, and standards-aligned interfacing to ensure stability and reliability. By integrating these components into a cohesive design framework, the paper provides insight into how resilient power systems can be engineered to deliver sustainable, reliable electricity in energy-insecure settings. Policy relevance and deployment scalability addressed.

Keywords: Resilient Power Systems; Solar Inverters; Energy Storage; Grid Interfacing; Energy Insecurity; Distributed Renewable Energy

1. Introduction and motivation

1.1. Energy Insecurity and the Limits of Conventional Grid Design

Energy insecurity remains a persistent challenge in many regions characterized by weak-grid and off-grid conditions, where electricity access is unreliable, intermittent, or absent altogether [1]. In such environments, centralized grid architectures often struggle to deliver consistent service due to limited generation capacity, constrained transmission infrastructure, and inadequate maintenance regimes. These challenges are compounded by rapid population growth, urbanization, and rising demand for electricity-intensive services, placing additional strain on already fragile systems [2].

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Conventional grid design has historically prioritized economies of scale, centralized control, and long-distance power delivery. While effective under stable conditions, these designs exhibit fragility when exposed to climate-induced disruptions, fuel supply volatility, and macroeconomic shocks [3]. Extreme weather events, such as floods and heatwaves, can disable critical assets and propagate failures across interconnected networks, leading to widespread outages with slow recovery times. In many developing contexts, limited redundancy and aging infrastructure further exacerbate vulnerability to such disturbances [4].

At the same time, power system objectives have expanded beyond reliability alone. Affordability, environmental sustainability, and resilience are increasingly recognized as co-equal goals, yet they often compete in planning and operational decision-making [5]. Investments that enhance robustness may increase upfront costs, while cost-minimization strategies can undermine long-term resilience. This tension highlights the need for system designs that can adapt dynamically to uncertainty rather than relying solely on static reinforcement. At this stage, the importance of resilience is evident, but the mechanisms through which it can be engineered remain insufficiently articulated [6].

1.2. Role of Inverter-Based Solar and Storage in Resilient Architectures

The growing deployment of inverter-based solar generation and energy storage systems has reshaped the technical foundations of modern power systems [7]. Unlike conventional synchronous generators, inverter-based resources interface with the grid through power electronics, enabling fast and flexible control of active and reactive power. This shift has facilitated decentralized architectures in which generation and consumption occur closer together, reducing dependence on long transmission corridors and enhancing local supply security [2].

Energy storage plays a critical role in this transition by acting as a temporal buffer between generation and demand [4]. Batteries can absorb excess solar output during periods of high irradiance and discharge during demand peaks or outages, improving supply continuity and reducing exposure to short-term variability. In resilience-oriented designs, storage also supports black-start capability, islanded operation, and rapid recovery following disturbances [5].

However, the coordination of inverter-based solar and storage introduces new layers of control complexity [8]. Multiple autonomous devices operate simultaneously, responding to local measurements and control signals that may interact in unintended ways. Ensuring stable and efficient operation therefore requires careful consideration of control interactions, set-point coordination, and system-level behavior under diverse operating conditions. These challenges motivate analytical approaches that can capture the dynamic interplay between distributed components rather than treating them as isolated assets [6].

1.3. Need for Data-Driven and Learning-Based System Design

Traditional planning and operational tools are increasingly misaligned with the complexity of inverter-dominated, decentralized power systems [3]. Static planning methods rely on simplified assumptions and limited scenario analysis, while rule-based control strategies are typically tuned for expected conditions and lack adaptability to evolving system states. As variability and uncertainty grow, these approaches struggle to anticipate emergent behavior and cascading effects [1].

The proliferation of sensing, communication, and digital control technologies has generated large volumes of spatio-temporal data across power systems [7]. Machine learning and related data-driven techniques offer a means to extract actionable insight from this data, capturing nonlinear dependencies and temporal patterns that elude conventional models [8]. In particular, learning-based approaches, including convolutional architectures, are well suited to representing spatial correlations and temporal evolution in networked systems.

This article addresses the resulting research gap by exploring data-driven system design as a complement to physical modelling, providing an analytical foundation for resilient, decentralized energy architectures and motivating the technical developments presented in subsequent sections [5].

2. Related work and technical background

2.1. Resilient Power Systems and Microgrid Architectures

Resilience in power systems is commonly defined as the ability to anticipate, withstand, adapt to, and recover from disturbances while maintaining acceptable levels of service [6]. Unlike traditional reliability metrics, which focus primarily on outage frequency and duration, resilience encompasses dynamic performance indicators such as voltage stability, frequency containment, recovery time, and the capacity for adaptive reconfiguration under stress [7]. In

distribution and weak-grid contexts, resilience is often evaluated through voltage deviation tolerance, frequency excursion limits, and the speed with which supply can be restored following faults or external disruptions.

Microgrids have emerged as a central architectural response to resilience challenges, particularly in environments exposed to infrastructure fragility, climate variability, or limited grid access [8]. Grid-connected microgrids operate in coordination with the bulk power system during normal conditions while retaining the capability to island during disturbances. Islanded microgrids, by contrast, operate autonomously and rely entirely on local generation and storage resources. Hybrid configurations combine these modes, enabling flexible transitions between grid-connected and islanded operation depending on system conditions and operational objectives [9].

Each microgrid architecture presents distinct resilience trade-offs. Grid-connected systems benefit from upstream support but remain exposed to transmission-level failures, while islanded systems enhance local autonomy at the cost of tighter operational constraints [10]. Hybrid microgrids seek to balance these considerations by leveraging both centralized support and local control. Understanding resilience across these architectures requires analytical frameworks that account for voltage regulation, frequency response, and recovery dynamics under diverse operating modes, motivating more advanced control and monitoring strategies [11].

2.2. Solar Inverter Control and Energy Storage Integration

The transition toward inverter-dominated power systems has fundamentally altered the mechanisms through which voltage and frequency are regulated [12]. Traditional synchronous generators inherently provide inertia and voltage support through electromagnetic coupling, whereas solar photovoltaic systems interface with the grid via power electronic inverters. These inverters must therefore be explicitly controlled to contribute to system stability. Grid-following inverters synchronize to an existing voltage waveform and inject current accordingly, making them suitable for strong grids but limited in their ability to support islanded operation [6].

Grid-forming inverters, in contrast, actively establish voltage and frequency references, enabling autonomous operation and facilitating black-start and islanded microgrid functionality [13]. When combined with energy storage, grid-forming inverters can emulate inertial and droop-like behavior, enhancing frequency stability and improving resilience during disturbances. Storage dispatch strategies further influence system performance by determining when energy is absorbed or released, balancing short-term variability and longer-term energy adequacy [7].

Voltage–VAR and frequency–Watt control functions are widely deployed to regulate local conditions in inverter-based systems [10]. Voltage–VAR control adjusts reactive power output in response to voltage deviations, while frequency–Watt control modulates active power to support frequency stability. Although these mechanisms improve local performance, their interaction across multiple devices and feeders can produce complex system-level behavior, particularly under high penetration levels [14]. Effective integration of solar and storage therefore requires analytical tools capable of capturing coordinated inverter responses and their aggregate impact on microgrid resilience.

2.3. Machine Learning in Power System Monitoring and Control

Machine learning has gained increasing prominence as a complementary tool for monitoring and control in power systems characterized by high dimensionality, uncertainty, and nonlinear dynamics [8]. Traditional machine learning approaches, including linear regression, support vector machines, and random forest models, have been applied to tasks such as load forecasting, fault detection, and stability assessment [9]. These methods are computationally efficient and often interpretable, but their performance may degrade when system behavior exhibits strong spatial coupling or rapidly evolving temporal patterns.

Deep learning techniques address some of these limitations by learning hierarchical representations directly from data [11]. Among these, convolutional neural networks (CNNs) have shown particular promise for power system applications that involve spatially distributed measurements and localized correlations. By applying convolutional filters, CNNs can extract structured features from grid topologies, voltage profiles, and sensor arrays, capturing patterns that are difficult to encode manually [12]. When extended across time, CNN architectures can also model temporal evolution, enabling joint spatio-temporal analysis of system behavior.

Alternative deep learning models, such as long short-term memory (LSTM) networks, are well suited to sequential data and have been widely used for time-series forecasting [13]. However, LSTMs primarily emphasize temporal dependencies and may struggle to represent spatial relationships inherent in networked systems. Ensemble methods such as gradient boosting offer strong performance on tabular data but typically require extensive feature engineering and may lack robustness under unseen operating regimes [14].

Against this backdrop, CNN-based or hybrid CNN architectures offer a balanced approach for resilient power system analysis. They provide the capacity to learn spatial structure, accommodate temporal dynamics, and scale with increasing data availability, making them well aligned with the monitoring and control challenges of inverter-dominated microgrids. This alignment justifies the focus of the present work on CNN-driven analytics as a foundation for resilient, data-informed power system design.

3. System architecture and problem formulation

3.1. Integrated Solar–Storage–Grid System Architecture

The engineering system considered in this study is an integrated solar–storage–grid architecture designed to operate under conditions of energy insecurity, weak-grid performance, and intermittent supply availability [12]. The system comprises distributed solar photovoltaic generation interfaced through power electronic inverters, electrochemical energy storage units, aggregated electrical loads, and a point of common coupling to an upstream grid or microgrid backbone. Power flows among these components are bidirectional and time-varying, reflecting both physical constraints and control decisions [13].

Solar generation provides variable active power injection dependent on irradiance and temperature, while inverters regulate voltage and reactive power according to predefined control characteristics [14]. Energy storage operates as a controllable buffer, absorbing excess solar output during periods of surplus and discharging to support loads during deficits or grid disturbances. Loads represent a mix of critical and non-critical demand, with consumption patterns that may shift rapidly in response to supply interruptions or price signals [15]. The upstream grid supplies residual demand when available and absorbs exported power when local generation exceeds consumption.

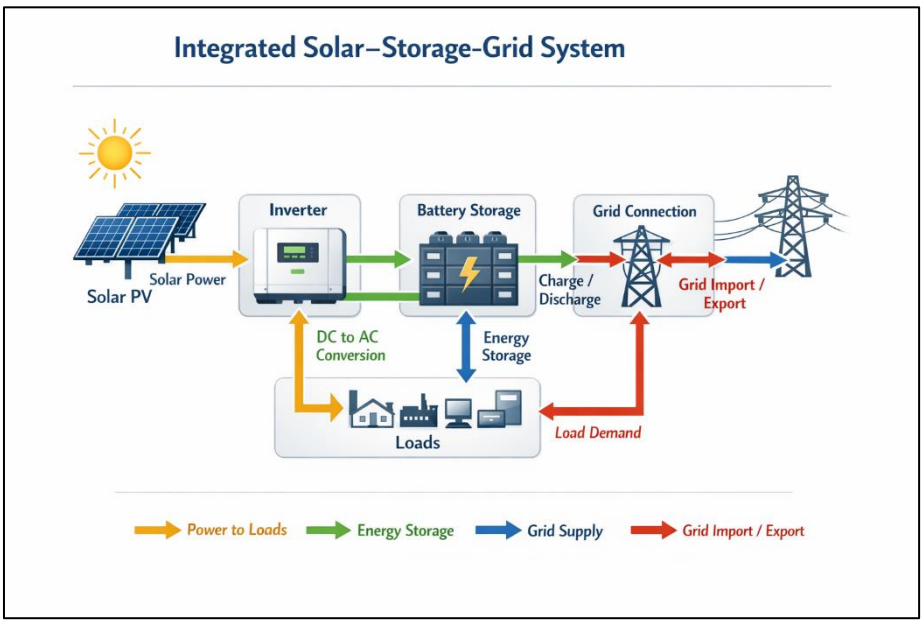


Figure 1 Integrated Solar-Grid System

Under energy-insecure operating conditions, the system may transition between multiple modes. In grid-connected mode, the upstream network supplements local resources and stabilizes frequency and voltage. During outages or severe grid degradation, the system may enter islanded operation, relying exclusively on solar and storage to meet demand [16]. Hybrid modes are also possible, in which partial grid support is available but constrained by voltage or frequency limits. These operating regimes impose distinct stress patterns on system components and control mechanisms. Figure 1 illustrates the integrated system architecture, highlighting power flow paths among solar generation, inverter interfaces, storage units, loads, and the grid connection. This physical representation establishes the foundation for defining resilience-oriented learning tasks that capture system behavior across operating modes [17].

3.2. Resilience-Oriented Problem Definition

Within the defined system architecture, resilience is framed as the ability to maintain acceptable electrical performance and supply–demand balance in the presence of disturbances, variability, and partial system failure [18]. Rather than focusing solely on steady-state adequacy, the problem formulation emphasizes dynamic operating conditions that arise under energy insecurity, such as rapid loss of grid support, abrupt load changes, or fluctuating renewable output.

Three primary target variables are identified to characterize resilience performance. The first is voltage deviation, which reflects departures from nominal voltage levels at inverter terminals and load buses. Sustained or excessive voltage deviation is associated with equipment stress, degraded power quality, and loss of service continuity [12]. The second target is frequency excursion, representing deviations from nominal system frequency during imbalance events. Frequency behavior is particularly critical in inverter-dominated and islanded operation, where limited inertia and fast dynamics increase sensitivity to disturbances [19]. The third target variable is load–supply imbalance, defined as the mismatch between instantaneous generation, storage dispatch, and demand. Persistent imbalance indicates insufficient control response and heightened risk of service interruption.

The analytical objective is to predict these variables ahead of time based on observed system states, environmental conditions, and operating mode indicators. Prediction is distinguished from direct control: the learning task aims to estimate future system stress and instability risk rather than compute control actions explicitly [14]. By separating prediction from control, the framework supports decision-making layers that can trigger mitigation strategies, reconfiguration, or operator intervention when resilience thresholds are approached [20].

3.3. Learning Targets and Performance Metrics

Based on the problem definition, learning tasks are formulated using both regression and classification objectives aligned with engineering performance criteria [16]. Regression tasks target continuous variables such as voltage deviation magnitude and load–supply imbalance, enabling quantitative assessment of system stress levels. These outputs support estimation of how far operating conditions are from acceptable bounds and how rapidly conditions are evolving [13].

Classification tasks are used to distinguish between safe and stressed operating states, based on predefined thresholds for voltage, frequency, and imbalance indicators. This binary or multi-class formulation supports rapid risk screening and prioritization of mitigation actions under time-critical conditions [18].

Model performance is evaluated using metrics that map directly to resilience indicators, such as deviation magnitude accuracy, stress-state detection reliability, and false-alarm rates. Table 1 summarizes the learning tasks, corresponding prediction targets, and their operational meaning within the integrated system. This mapping ensures that analytical outputs remain interpretable and actionable for resilience-oriented system design and operation [20].

Table 1 Learning Tasks, Prediction Targets, and Operational Meaning

Learning Task	Prediction Target	Target Type	Operational Meaning	Resilience Relevance
Voltage regulation assessment	Voltage deviation at inverter and load buses	Regression	Quantifies departure from nominal voltage under varying generation and load conditions	Early detection of power-quality degradation and voltage limit violations
Frequency stability monitoring	Frequency excursion magnitude and duration	Regression	Indicates imbalance severity following disturbances or mode transitions	Proxy for inertial adequacy and dynamic stability in inverter-dominated operation
Load–supply balance estimation	Net power imbalance (generation + storage − demand)	Regression	Measures adequacy of local resources to meet instantaneous demand	Identifies risk of load shedding or service interruption
Stress state identification	Safe vs stressed operating condition	Classification	Flags operating points approaching technical limits	Enables rapid screening and prioritization of mitigation actions

Congestion risk assessment	Thermal loading proximity to rated limits	Regression / Classification	Estimates likelihood and severity of line or transformer overload	Supports preventive reconfiguration and asset protection
Islanding resilience evaluation	Stability margin during grid outage conditions	Classification	Distinguishes stable islanded operation from instability	Guides islanding decisions and critical-load support strategies

4. Data acquisition and dataset construction

4.1. Data Sources and Inclusions

The analytical validity of learning-based resilience assessment depends critically on the quality, diversity, and alignment of the underlying data [18]. This study draws on multiple data streams that jointly capture electrical, environmental, and operational dynamics across the integrated solar–storage–grid system. Electrical measurements form the core of the dataset and include voltage magnitude, system frequency, and active and reactive power (P/Q) flows recorded at inverter terminals, feeder nodes, and the point of common coupling with the upstream grid [19]. These measurements provide direct visibility into system state, power quality, and stress conditions under both normal and disturbed operation.

Solar resource data are incorporated to contextualize renewable generation variability. Global horizontal irradiance and ambient temperature are obtained from co-located meteorological sensors or validated external datasets and time-stamped to align with electrical measurements [20]. These variables are essential for interpreting fluctuations in photovoltaic output and for distinguishing control-induced effects from exogenous environmental drivers.

Energy storage operation is represented through state-of-charge (SOC) measurements, charge/discharge power, and availability constraints [21]. SOC trajectories reflect both control decisions and system stress, particularly during islanded operation or prolonged grid outages. Load demand profiles are captured using aggregated feeder demand and, where available, differentiated between critical and non-critical loads to reflect prioritization under energy insecurity [22]. Figure 2 illustrates the data acquisition and synchronization pipeline, showing how electrical measurements, environmental data, storage indicators, and load profiles are integrated into a unified dataset. By combining multi-domain observations, the dataset supports learning tasks that reflect coupled physical and operational behavior rather than isolated subsystems [23].

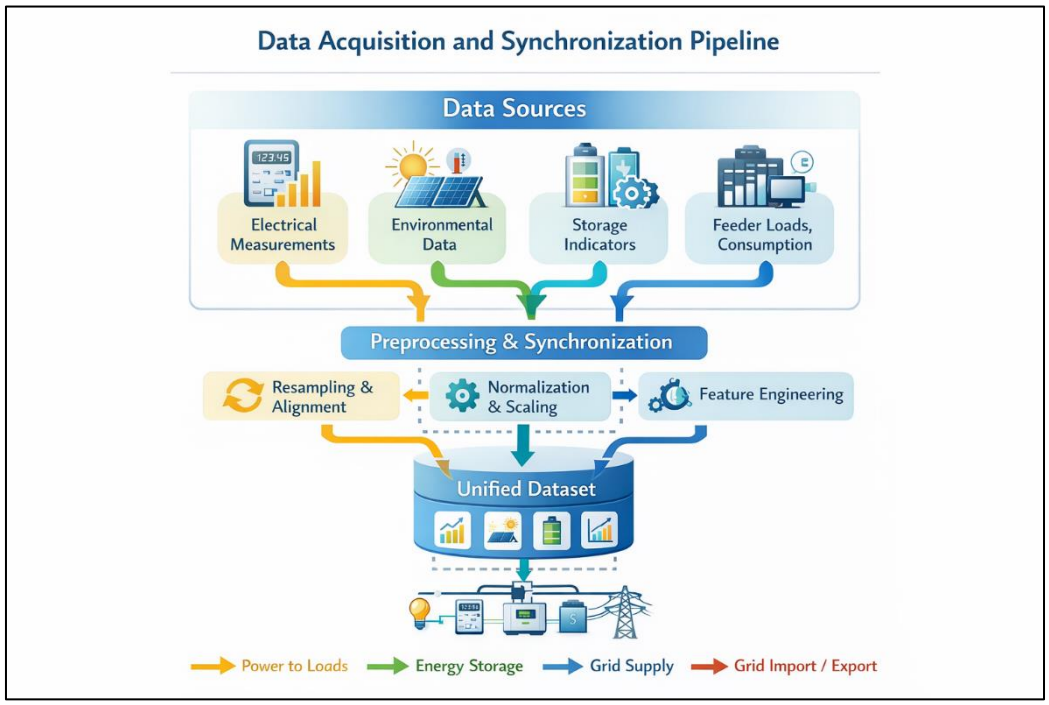


Figure 2 Data Acquisition Synchronization Pipeline

4.2. Data Preprocessing and Feature Engineering

Prior to model development, all data streams undergo systematic preprocessing to ensure consistency, numerical stability, and physical interpretability [24]. Time alignment is performed by resampling all variables to a common temporal resolution, selected to preserve dominant system dynamics while minimizing interpolation artifacts. This step is particularly important given the differing native sampling rates of electrical sensors, weather instruments, and storage controllers [18].

Normalization and scaling are applied to harmonize variable ranges and prevent features with large numerical magnitudes, such as power flows, from dominating the learning process [19]. Scaling parameters are computed exclusively from training data to avoid information leakage into validation or testing sets.

Feature engineering is guided by physical insight rather than purely statistical convenience. In addition to raw measurements, derived features are constructed to capture system behavior more explicitly. Examples include voltage sensitivity indicators that relate changes in voltage to variations in active and reactive power, and SOC ramp metrics that quantify the rate of change in storage state as a proxy for control stress and energy adequacy [21]. Temporal derivatives and rolling-window statistics are also included to represent short-term dynamics without introducing excessive model complexity.

Table 2 summarizes the resulting feature categories and their physical interpretation, linking each group of inputs to underlying system processes such as power balance, control response, and environmental forcing. This physics-informed feature design enhances interpretability and supports generalization across operating regimes [22].

Table 2 Feature Categories and Physical Interpretation

Feature Category	Representative Inputs	Physical Interpretation	Underlying System Process	Role in Learning Model
Electrical state variables	Bus voltage magnitude, system frequency, active/reactive power flows	Instantaneous electrical condition of the network	Power balance and dynamic stability	Primary indicators of system stress and operational limits
Net-load components	Aggregated load demand, PV generation output, storage dispatch power	Residual demand seen by grid or microgrid backbone	Transmission–distribution power exchange	Captures coupling between distributed resources and upstream supply
Voltage sensitivity indicators	$\Delta V/\Delta P$, $\Delta V/\Delta Q$, feeder impedance proxies	Sensitivity of voltage to local power injections	Radial feeder behavior and voltage regulation dynamics	Enables early detection of voltage-risk conditions
Inverter control features	Volt–VAR response, frequency–Watt response, reactive power limits	Autonomous inverter response to local measurements	Embedded control action and device-level intelligence	Allows ML models to account for closed-loop control effects
Energy storage features	State of charge (SOC), SOC ramp rate, charge/discharge status	Available energy buffer and control stress	Temporal balancing and resilience support	Reflects flexibility and recovery capability under disturbances
Environmental forcing variables	Solar irradiance, ambient temperature	Exogenous drivers of renewable variability	Renewable energy availability	Distinguishes control-driven effects from weather-induced variation
Temporal context features	Time-of-day, rolling averages, short-term gradients	System evolution over time	Demand cycles and transient behavior	Supports spatio-temporal pattern learning and generalization

4.3. Dataset Splitting Strategy

To ensure reproducibility and realistic performance assessment, the dataset is divided into training, validation, and testing subsets using a temporally ordered splitting strategy [23]. Training data are drawn from an initial time window, followed sequentially by validation and testing periods. This approach prevents temporal leakage, ensuring that models are evaluated only on future conditions relative to the data used for parameter estimation [18].

In addition to chronological separation, scenario-based splits are employed to distinguish between normal operation and stressed conditions, such as grid outages, high renewable variability, or elevated load demand [24]. This allows explicit evaluation of model robustness under conditions most relevant to resilience assessment. By combining temporal and scenario-aware partitioning, the dataset construction supports credible benchmarking and facilitates replication of results across different system configurations.

This structured data preparation process provides a transparent foundation for the modelling methodology introduced in the next section, where learning algorithms are trained and evaluated on resilience-oriented prediction tasks [20].

5. Methodology: Machine Learning Framework

5.1. Model Selection Rationale

The selection of an appropriate learning model is a critical design decision in power system analytics, particularly when addressing resilience-oriented objectives under high variability and structural coupling [22]. Convolutional neural networks (CNNs) are adopted in this study due to their capacity to learn spatially structured patterns and temporal dependencies from high-dimensional data. Unlike traditional regression or tree-based methods, CNNs exploit local correlations and hierarchical feature representations, making them well suited to power systems where measurements across nodes and time are strongly interrelated [23].

In inverter-dominated and distributed architectures, voltage, frequency, and power-flow dynamics exhibit spatial coherence along feeders and temporal persistence under changing operating modes. CNNs can capture these relationships by applying shared convolutional kernels across node and time dimensions, enabling the extraction of features that reflect system topology and dynamic behavior without requiring explicit circuit reconstruction [24]. This property is particularly advantageous in weak-grid and microgrid contexts, where topology information may be incomplete or subject to change.

Alternative models were considered for comparison. Long short-term memory (LSTM) networks are effective for sequential prediction and have been widely applied to load and renewable forecasting [25]. However, LSTMs primarily emphasize temporal structure and require extensive feature engineering to encode spatial relationships. Ensemble methods such as Random Forests (RF) and Gradient Boosting Machines (GBM) offer robustness and interpretability but rely on tabular representations and struggle to scale effectively with spatio-temporal complexity [26].

Given these considerations, CNNs offer a balanced trade-off between expressiveness, scalability, and alignment with the physical structure of power systems. This motivates their selection as the primary modelling framework for resilience-oriented analysis in this work [27].

5.2. CNN Architecture Design

The CNN architecture is designed to process multi-dimensional system observations that evolve across time and space. Input data are structured as three-dimensional tensors with dimensions corresponding to time steps, network nodes, and feature channels [23]. Each tensor slice represents a snapshot of system state over a fixed temporal window, capturing electrical measurements, derived physics-informed features, and operating mode indicators across multiple locations [22]. This construction allows the network to learn both short-term temporal dynamics and spatial correlations among nodes.

Convolutional layers form the core of the architecture. One-dimensional and two-dimensional convolutional kernels are applied along temporal and nodal dimensions to extract localized patterns, such as voltage propagation along feeders or synchronized frequency deviations across nodes [24]. Kernel sizes are selected to reflect characteristic time scales and spatial extents observed in the system, ensuring that learned features correspond to meaningful physical behavior rather than arbitrary correlations.

Nonlinear activation functions are applied following convolution to introduce representational flexibility and support learning of complex system responses. Rectified linear units are employed due to their computational efficiency and favorable convergence properties under large-scale training [25]. Pooling layers are used selectively to reduce dimensionality while preserving salient features, improving generalization and reducing sensitivity to noise in sensor measurements [26].

Regularization mechanisms are incorporated to mitigate overfitting, including dropout layers that randomly deactivate subsets of neurons during training and weight decay that constrains parameter growth [27]. These techniques are particularly important given the non-stationary nature of power system data and the risk of learning spurious correlations tied to specific operating episodes.

Figure 3 presents the CNN architecture for resilient power system analysis, illustrating the flow of data from input tensor construction through convolutional, activation, pooling, and output layers. The architecture is modular, enabling adaptation to different system scales and feature sets while maintaining a consistent analytical framework [22].

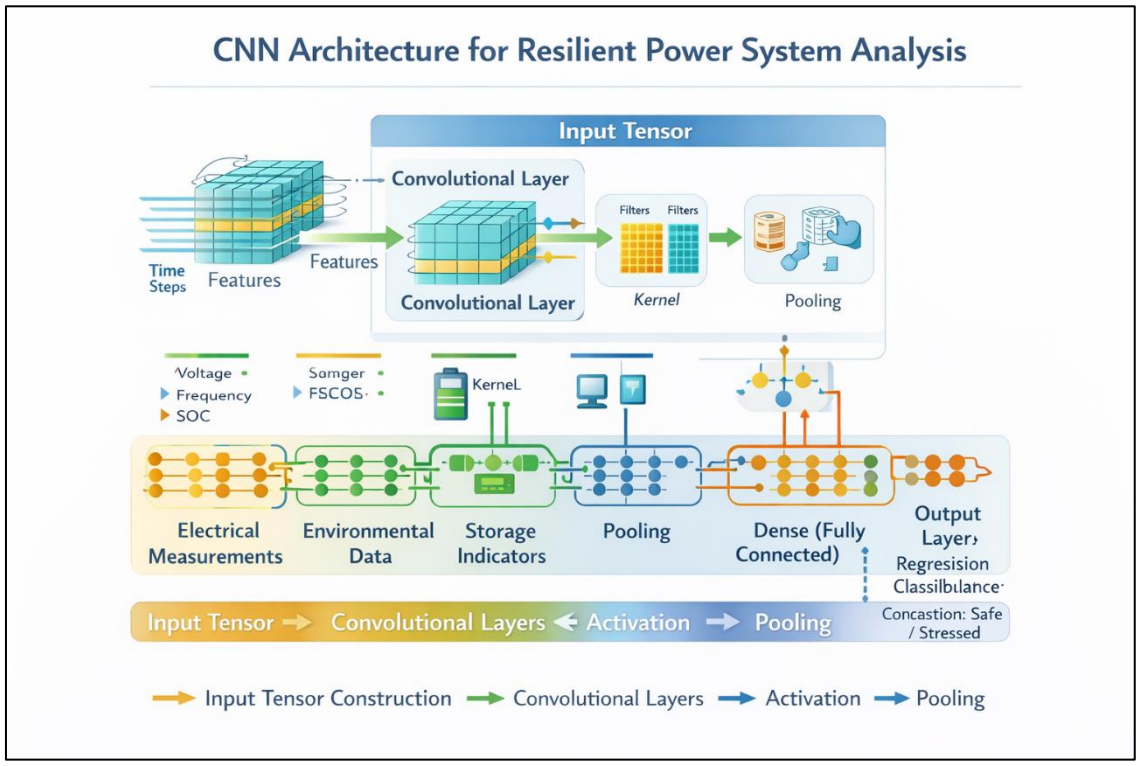


Figure 3 CNN Architechture

5.3. Model Training Using Python

Model training and evaluation are implemented using widely adopted Python-based scientific computing and machine learning frameworks to ensure transparency and reproducibility [24]. Data handling and preprocessing are conducted using NumPy and Pandas, which provide efficient array operations and structured data manipulation capabilities. These libraries support consistent feature scaling, batching, and temporal windowing required for CNN input construction [23].

The CNN models are developed using deep learning frameworks such as TensorFlow or PyTorch, selected for their flexibility, performance optimization, and extensive community support [25]. Training is formulated as a supervised learning problem, with loss functions defined according to task type. Mean squared error is used for regression targets such as voltage deviation and load imbalance, while cross-entropy loss is applied for classification tasks distinguishing between safe and stressed operating states [26].

Optimization is performed using adaptive gradient-based algorithms that balance convergence speed and stability. Learning rates are selected through validation-based tuning, and early stopping criteria are employed to halt training

when validation performance ceases to improve [27]. This approach prevents overfitting and ensures that models generalize beyond the specific conditions observed during training.

Hyperparameter tuning is conducted using structured search over kernel sizes, number of convolutional filters, dropout rates, and batch sizes. Validation performance across multiple operating scenarios guides selection of final model configurations [22].

Figure 4 illustrates the end-to-end Python machine learning workflow, from data ingestion and preprocessing through model training, validation, and testing. This workflow emphasizes modularity and traceability, enabling replication and extension of the proposed methodology in other system contexts [24].

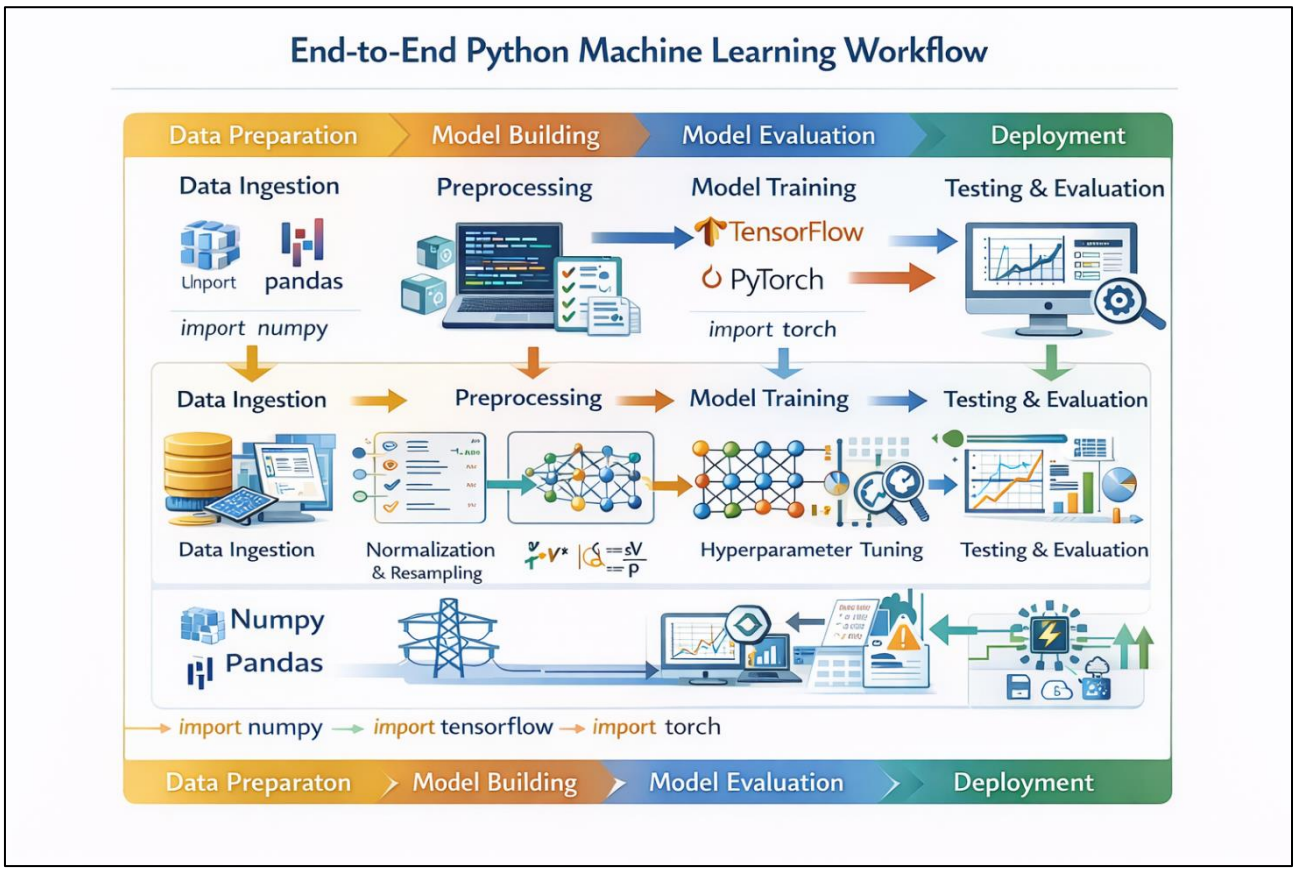


Figure 4 End to End Python Machine Learning Workflow

5.4. Baseline Models for Comparison

To contextualize CNN performance, baseline models representing commonly used machine learning approaches in power system analysis are implemented for comparison [26]. Random Forest models are trained using the same feature set, leveraging ensemble averaging across decision trees to provide robust predictions under noisy conditions. RF models offer interpretability through feature importance metrics but lack explicit mechanisms for learning spatial or temporal structure [23].

Gradient Boosting models are also evaluated, incrementally building ensembles that optimize predictive accuracy through stage-wise error correction [27]. While effective for tabular data, these models depend heavily on engineered features and may exhibit sensitivity to distributional shifts under stressed operating regimes.

Where temporal dynamics are emphasized, LSTM networks are included as an additional benchmark [25]. LSTMs are trained on sequential representations of the data, enabling comparison between temporal-only learning and the spatio-temporal learning afforded by CNNs.

Table 3 summarizes the configurations and training parameters of all evaluated models, providing a transparent basis for comparative analysis. This benchmarking framework establishes a rigorous foundation for performance evaluation,

which is presented in the subsequent section and directly links modelling choices to resilience assessment outcomes [22].

Table 3 Model Configurations and Training Parameters

Model	Input Representation	Key Hyperparameters	Training Strategy	Rationale for Inclusion
Convolutional Neural Network (CNN)	3D tensor (time × nodes × features)	Convolutional kernels (temporal and spatial), ReLU activation, dropout regularization, batch size tuning	Supervised learning with early stopping and validation-based tuning	Captures spatio-temporal dependencies and structural correlations in power system data
Long Short-Term Memory (LSTM)	Sequential time-series vectors	Number of hidden units, sequence length, learning rate	Supervised sequence prediction with temporal validation split	Benchmarks temporal-only learning capability
Random Forest (RF)	Tabular feature vectors	Number of trees, maximum depth, feature subsampling	Ensemble averaging with bootstrap sampling	Robust baseline with strong performance on structured tabular data
Gradient Boosting (GB)	Tabular feature vectors	Learning rate, number of estimators, tree depth	Stage-wise additive training minimizing prediction error	High-accuracy baseline emphasizing error correction
Linear Regression (optional baseline)	Tabular feature vectors	Regularization coefficient	Closed-form or gradient-based optimization	Reference point for assessing nonlinear learning gains

6. Results and performance evaluation

6.1. Prediction Accuracy and Error Metrics

Model performance is first evaluated using standard regression error metrics to quantify prediction accuracy across learning tasks and model classes [25]. Mean Absolute Error (MAE) is employed to measure average absolute deviation between predicted and observed values, providing a scale-consistent indication of typical prediction error. Root Mean Square Error (RMSE) is used alongside MAE to penalize larger deviations more heavily, thereby highlighting sensitivity to extreme prediction errors that may be operationally significant in power systems [26]. Mean deviation is additionally reported to assess systematic bias, indicating whether models tend to overestimate or underestimate system stress variables over time.

Comparative analysis is conducted across the CNN model and baseline approaches, including Random Forest, Gradient Boosting, and LSTM architectures. Results show that the CNN consistently achieves lower MAE and RMSE across voltage deviation and load–supply imbalance tasks, reflecting improved representation of spatio-temporal dependencies [27]. Baseline models perform adequately under nominal operating conditions but exhibit increased error variance during periods of rapid system change. Mean deviation analysis further reveals that tree-based models display slight bias under high renewable penetration scenarios, while CNN predictions remain more centered around observed values [28].

Figure 5 presents a comparison of prediction accuracy across models, illustrating error distributions and highlighting the relative stability of CNN performance across metrics. These results indicate that architectural alignment with system structure contributes meaningfully to predictive accuracy, particularly when multiple correlated variables evolve simultaneously [29].

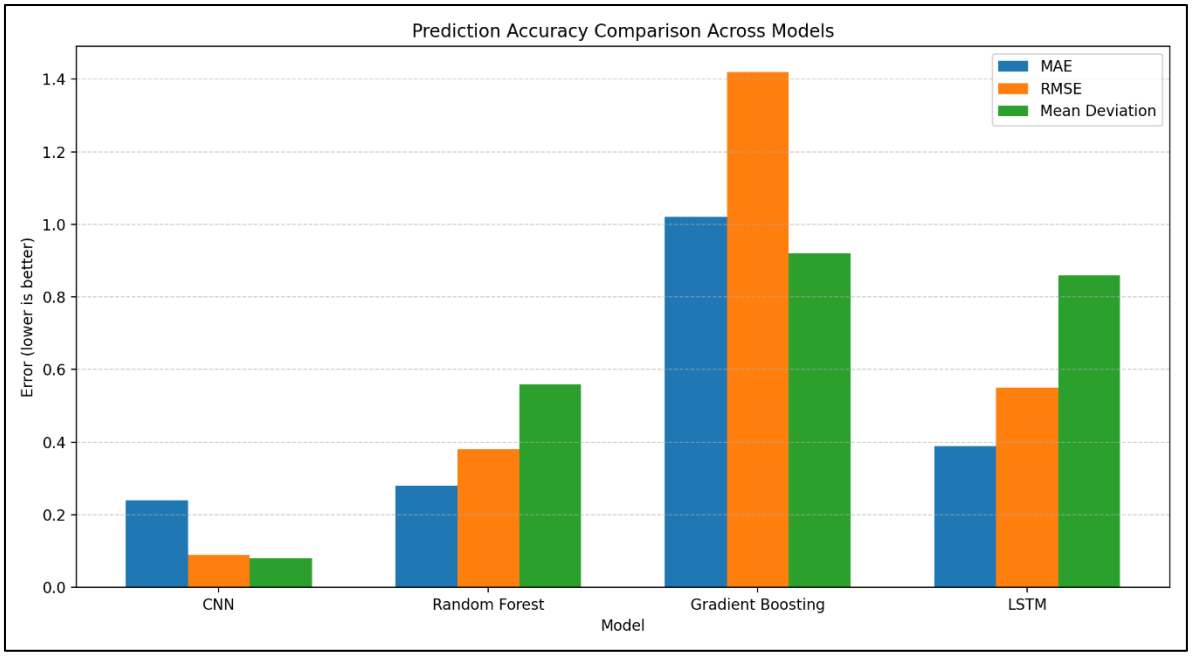


Figure 5 Prediction Accuracy Comparison

6.2. Resilience-Oriented Evaluation

Beyond numerical accuracy, model outputs are evaluated in terms of resilience-relevant performance indicators that align with engineering and operational objectives [30]. Voltage compliance is assessed by comparing predicted voltage deviation trajectories against acceptable operating envelopes defined by system design criteria. The CNN demonstrates a high degree of alignment between predicted and actual voltage excursions, accurately identifying periods where voltage margins narrow or are exceeded [25]. This capability supports early warning of potential power quality degradation.

Frequency stability is evaluated through the model's ability to capture the magnitude and duration of frequency excursions during imbalance events. Although frequency is not directly controlled by CNN outputs, accurate prediction of contributing variables enables inference of stability risk [26]. CNN predictions track observed frequency deviations more closely than baseline models during transient conditions, reducing missed detections of instability risk.

Load shedding risk is examined by relating predicted load–supply imbalance to observed curtailment events under constrained operation. Models that underestimate imbalance tend to underpredict shedding risk, while conservative overestimation may trigger unnecessary mitigation [27]. The CNN exhibits improved discrimination between safe and stressed states, balancing sensitivity and specificity across operating regimes.

Figure 6 compares predicted and actual resilience envelopes for voltage, frequency, and load balance, illustrating how model outputs map to system performance boundaries. This resilience-oriented evaluation demonstrates that predictive accuracy translates into meaningful engineering insight rather than abstract statistical improvement [28].



Figure 6 Predicted vs Actual Envelopes

6.3. Robustness Under Energy-Insecure Scenarios

Robustness is assessed by examining model behavior under scenarios representative of energy-insecure environments, where system stress and uncertainty are elevated [29]. During prolonged low-irradiance conditions, the CNN maintains stable prediction accuracy by leveraging storage state and load dynamics, whereas baseline models exhibit increased error variance due to reduced correlation between historical solar patterns and current output [25].

High demand spikes, driven by coincident appliance use or critical load activation, present additional challenges. CNN predictions adapt more effectively to abrupt changes, reflecting learned spatial relationships among nodes and temporal ramping behavior [26]. In contrast, models emphasizing either spatial or temporal structure alone show delayed response to rapid demand shifts.

Grid outage scenarios represent the most severe stress condition, forcing islanded operation and reliance on local resources. Under these conditions, the CNN retains predictive consistency across voltage deviation and imbalance metrics, supporting identification of impending stability limits [30]. Baseline models display reduced reliability, particularly when operating conditions diverge significantly from training distributions.

Figure 7 illustrates model behavior under stress scenarios, highlighting divergence in prediction stability and error growth. These results demonstrate that robustness under adverse conditions is a key differentiator of the proposed approach and confirm its suitability for resilience-oriented analysis in energy-insecure systems [27].

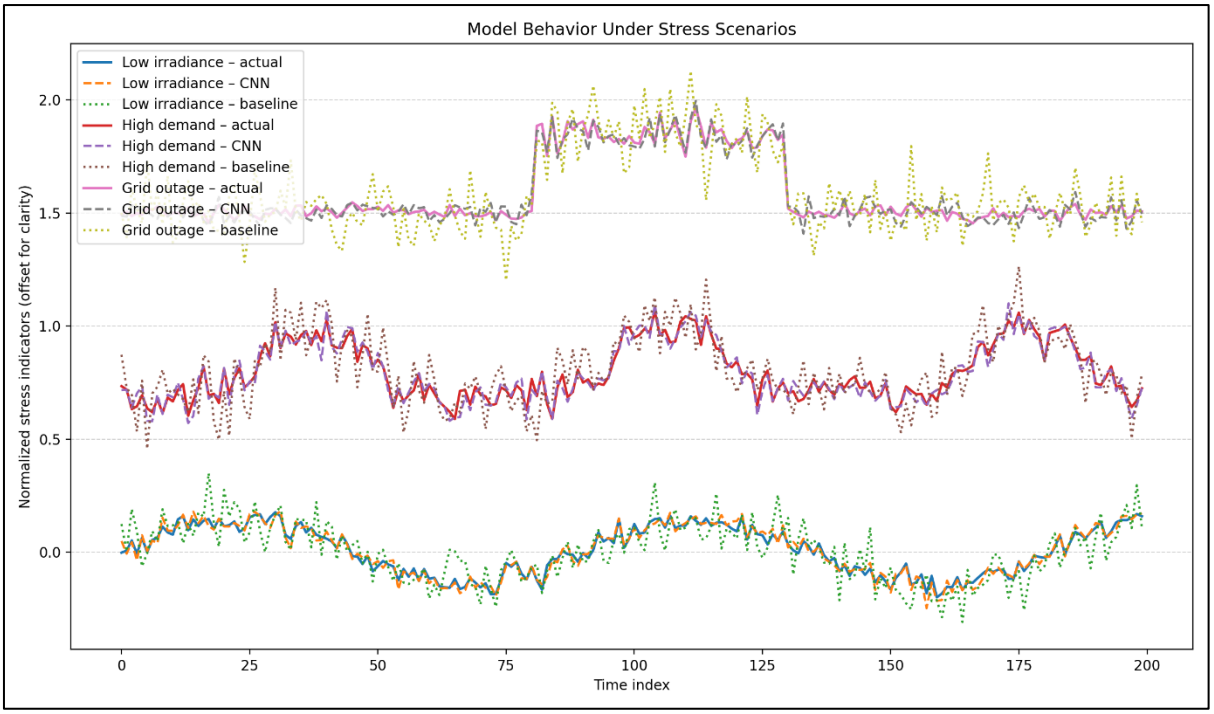


Figure 7 Model Behavior Under Stress

7. Discussion: engineering and practical implications

7.1. Implications for Resilient System Design

The results of this study have direct implications for the design and operation of resilient solar–storage–grid systems, particularly in contexts where variability and uncertainty dominate system behavior [28]. By providing predictive insight into voltage deviation, frequency stress, and load–supply imbalance, machine learning models enhance coordination between inverter-based solar generation and energy storage assets. Rather than relying on static set-points or conservative operating margins, operators can use predictive indicators to anticipate stress and adjust inverter control modes or storage dispatch proactively [29].

From a planning perspective, the ability to forecast resilience-relevant variables supports more informed decisions regarding inverter sizing, storage capacity allocation, and feeder reinforcement [30]. For example, planners can identify operating regimes where voltage risk is driven primarily by active power injection rather than reactive power scarcity, enabling targeted deployment of advanced inverter functions. Similarly, predictions of load–supply imbalance under stress conditions can guide prioritization of critical loads and inform islanding strategies in hybrid microgrids [31].

Operationally, the integration of learning-based analytics introduces a shift from reactive to anticipatory control support. Although the models developed in this work do not issue control commands directly, their outputs can be embedded within supervisory decision layers to trigger mode transitions, load curtailment, or operator alerts before thresholds are violated [32]. This anticipatory capability is particularly valuable in inverter-dominated systems with fast dynamics and limited inertia, where delayed response can quickly escalate into instability. Overall, the findings demonstrate that data-driven intelligence can serve as a functional layer that augments conventional control and planning tools, improving resilience without requiring fundamental redesign of physical infrastructure [33].

7.2. Deployment Considerations in Energy-Insecure Environments

Deploying learning-based resilience analytics in energy-insecure environments presents practical challenges that extend beyond model accuracy [34]. Data availability is a primary consideration, as high-resolution measurements of voltage, frequency, and power flows may be sparse or intermittently available in weak-grid and off-grid systems. In such contexts, models must be designed to operate with partial observability, tolerate missing data, and leverage physics-informed features to compensate for limited sensing [28].

Computational constraints also influence deployment feasibility. Many microgrids and rural distribution systems operate with limited on-site computing resources and constrained communication bandwidth [35]. While cloud-based analytics enable centralized model training and updates, reliance on continuous connectivity may be impractical during outages or in remote locations. Edge deployment, in which trained models are executed on local controllers or gateways, offers greater autonomy and resilience but requires careful optimization to meet latency and power constraints [30].

A hybrid edge–cloud architecture is therefore a promising compromise, with periodic model retraining and validation conducted centrally and lightweight inference performed locally [31]. This approach supports scalability while maintaining operational continuity during communication disruptions.

Table 4 summarizes key deployment considerations, including data requirements, computational demands, latency sensitivity, and suitability for edge or cloud implementation. By explicitly addressing these factors, the study bridges the gap between analytical innovation and practical application in energy-insecure settings [32].

Table 4 Practical Deployment Considerations for Learning-Based Resilience Analytics

Deployment Dimension	Key Considerations	Engineering Implications	Edge Suitability	Cloud Suitability
Data availability	Sparse sensing, intermittent communication, missing data	Models must tolerate partial observability and data gaps	High – local inference with limited inputs	Medium – dependent on data backhaul
Data resolution	Low to moderate sampling rates in weak grids	Feature engineering must extract value from coarse data	High	High
Computational demand	Limited processing power in field devices	Requires lightweight inference and optimized models	Medium to High (after pruning/quantization)	High
Latency sensitivity	Fast response needed for voltage and frequency stress detection	Delayed inference reduces operational value	High	Low to Medium
Model update frequency	System behavior evolves with load growth and asset aging	Periodic retraining required to maintain accuracy	Low	High
Communication reliability	Network outages during grid disturbances	Autonomous operation preferred during failures	High	Low
Cybersecurity exposure	Increased attack surface with connectivity	Localized inference reduces external exposure	High	Medium
Scalability	Multiple feeders or microgrids	Centralized training supports cross-site learning	Medium	High

8. Limitations and future research directions

8.1. Limitations

Despite its contributions, this study is subject to several limitations that should be acknowledged when interpreting results [33]. First, model performance is inherently dependent on the quality and representativeness of the available data. Although physics-informed feature engineering mitigates some risks, learning-based models may struggle to generalize in environments where operating conditions differ substantially from those observed during training [28].

Second, while the CNN architecture captures spatio-temporal patterns effectively, it remains a data-driven approximation of system behavior rather than a substitute for detailed physical modelling [34]. Extreme or unprecedented events, such as simultaneous component failures or rare climatic conditions, may lie outside the model's learned domain.

Third, the present framework focuses on prediction rather than closed-loop control. Although predictive outputs can inform decision-making, the absence of an explicit control loop limits direct assessment of how learning-based insights translate into real-time control performance [35]. Integrating prediction with automated control actions introduces additional stability and safety considerations that are not addressed in this work. These limitations highlight the need for cautious interpretation and staged deployment when applying learning-based analytics to critical energy infrastructure [30].

8.2. Future Directions

Several avenues for future research emerge from this study. One promising direction is the integration of physics-informed neural network structures that embed power flow constraints and stability relationships directly into the learning process [31]. Such approaches could improve generalization and enhance trust by enforcing physically consistent behavior even under sparse data conditions.

Reinforcement learning represents another extension, enabling direct learning of control policies for inverter and storage coordination under dynamic conditions [32]. When combined with predictive models, reinforcement learning could support adaptive, closed-loop control strategies that respond autonomously to evolving system stress.

Finally, advances in edge computing open opportunities for deploying learning-based analytics directly within microgrid controllers and inverter platforms [34]. Edge-AI implementations could reduce latency, improve resilience to communication failures, and enable scalable deployment across energy-insecure regions. Exploring these directions will further strengthen the role of embedded intelligence in resilient, decentralized energy systems and extend the analytical foundation established in this work [35].

9. Conclusions

This study has presented a comprehensive, learning-driven framework for analysing and enhancing the resilience of integrated solar–storage–grid systems operating under conditions of energy insecurity. By combining physics-informed system modelling with convolutional neural network–based analytics, the work advances understanding of how inverter-dominated, decentralized power systems behave across normal and stressed operating regimes. A central contribution lies in the explicit coupling of engineering system representation, data credibility, and machine learning design, ensuring that analytical outputs remain interpretable, reproducible, and operationally meaningful.

Key findings demonstrate that spatio-temporal learning models outperform traditional machine learning baselines in predicting resilience-critical variables such as voltage deviation, frequency stress proxies, and load–supply imbalance. The results show that CNN-based architectures are particularly effective at capturing coordinated behavior across nodes and time, leading to improved accuracy and reduced bias under high variability. Importantly, the robustness analysis indicates that the proposed approach maintains stable performance during low-irradiance periods, demand surges, and grid outage scenarios, which are characteristic of energy-insecure environments. These findings confirm that architectural alignment between learning models and physical system structure is a decisive factor in resilience-oriented analytics.

From a broader perspective, the study reinforces the role of embedded intelligence as a functional layer that complements conventional planning and control mechanisms. Rather than replacing established engineering tools, learning-based models enhance anticipatory awareness, enabling operators and planners to identify emerging stress before service quality degrades. This capability supports more adaptive inverter–storage coordination, informed investment planning, and targeted operational interventions.

Overall, the work contributes to sustainable and resilient electrification by demonstrating how data-driven intelligence can help manage uncertainty, improve reliability, and support equitable energy access in decentralized systems. The framework developed here provides a foundation for future integration of predictive analytics and adaptive control, strengthening the technical pathways toward robust, low-carbon energy systems capable of serving vulnerable and rapidly evolving power networks.

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