Real time grid stability and frequency regulation for outage minimization using hybrid neural architecture

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Abstract - **The growing complexity of modern smart grids and increasing penetration of renewable energy sources have made real-time stability and frequency regulation critical for preventing large-scale outages. Traditional control systems often fail to respond quickly to sudden disturbances, resulting in delayed correction and higher outage risk. To address this challenge, the present work proposes a hybrid neural architecture that integrates CNN and RNN models to enhance prediction accuracy and response speed for real-time grid stability assessment. Using the UCI Electrical Grid Stability Simulated Dataset, the study performs comprehensive preprocessing including normalization, feature extraction, label encoding, and class balancing, followed by training of CNN, RNN, and hybrid models on a 60–40 train–test split. The hybrid model leverages spatial–temporal learning to detect early instability patterns with high reliability. Experimental results show that the proposed hybrid model achieves 94% accuracy, 92% precision, 90% recall, and 91% F1-score, outperforming individual models. Latency is maintained at 8 ms, enabling rapid detection of frequency deviations and supporting real-time outage minimization in dynamic grid environments.**

Keywords: Real-time grid stability, Frequency regulation, Hybrid neural network, CNN–RNN model, Electrical Grid Stability Dataset

I. INTRODUCTION

The stability of real-time is one of the issues that are harder to maintain in current electrical grids because of the increasing demand, penetration of renewable energy sources, and the increased complexity of distributed generation [1]. Conventional measurement and monitoring systems are based on the predetermined rules and fixated system models that are hard to react to the sudden the disturbances, the load changes, and the unexpected outages. With the grids becoming increasingly decentralized and automated, intelligent systems that can constantly learn and adapt are needed to ensure the reliability in operations and reduction of service interruptions [2].

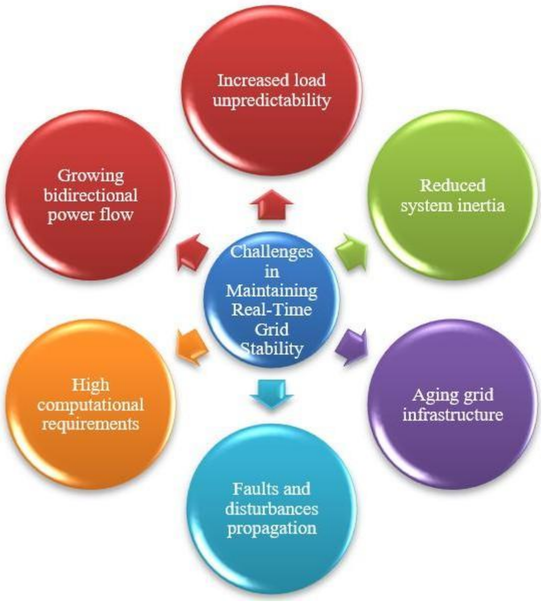


Figure 1: Challenges in Maintaining Real-Time Grid Stability

System frequency is one of the key measurements of grid health, and it should not be allowed to fall outside a tight range, or it can cause multiple failures [3]. Frequency deviations can happen in milliseconds when the supply and demand are out of balance that requires equally swift corrective measures. Traditional frequency control systems like primary and secondary control loops tend to have slow response times and poor predictive ability [4]. These constraints create instability with large impacts, e.g., generator trips or abrupt renewable power outages. Therefore, there is an evident necessity of more sophisticated, data-based models that would be able to predict deviations and perform correction operations more quickly and accurately.

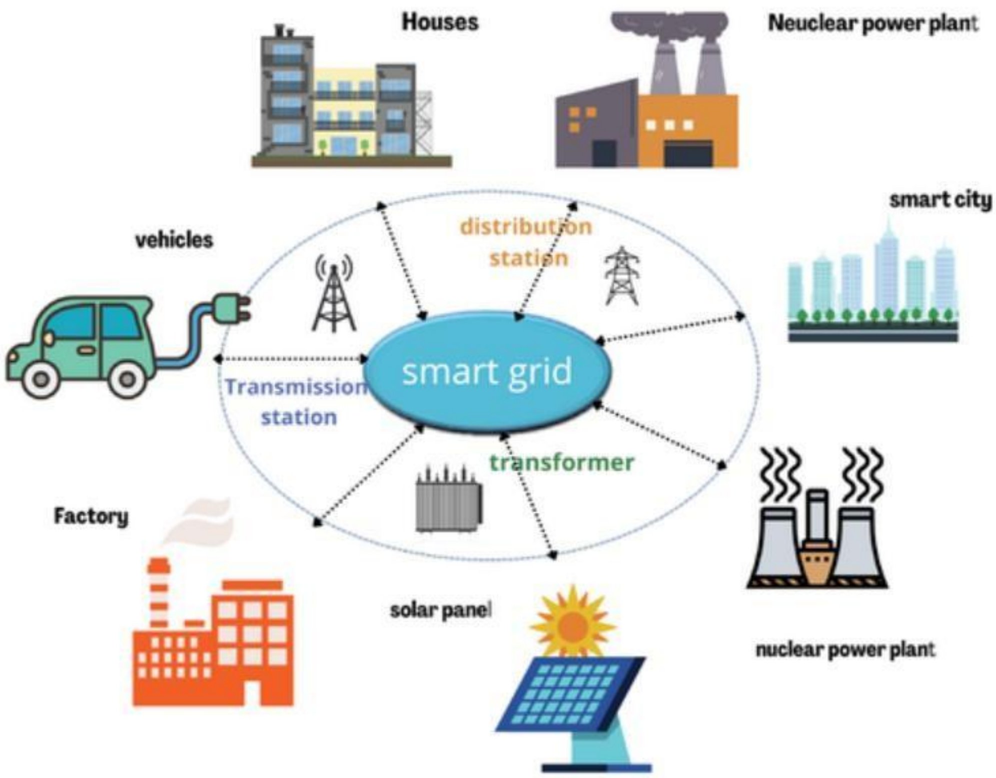


Figure 2: Overview of Smart grid [5]

Architectures based on neural networks have become promising to represent extremely nonlinear, dynamic systems such as power grids. Single-model methods, however, can frequently be difficult to scale across different operating conditions or present complicated temporal relationships in high-resolution grid data. A promising direction is the integration of various models (so-called hybrid neural architectures) into an alternative: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and attention, etc. [6]. Such systems integrate spatial feature learning, learning a temporal sequence, and detecting anomalies in real time, which allows much more accurate and proactive regulation of the frequency. The particular research is aimed at creating a hybrid model of the neural architecture, which is capable of real-time monitoring of grid conditions, forecasting frequency deviations, and automatically taking corrective measures to avoid outages [7]. The proposed framework would use high-frequency telemetry, disturbance history, and adaptive learning processes to improve grid resilience by a significant margin. By doing this, it offers a smart decision-support system to the utilities that can reduce the rate of downtimes, eliminate massive blackouts, and provide steady and consistent supply of power in the ever-involved grid systems [8].

The research starts by introducing the reality of grid stability issues and literature devoted to them, then the hybrid neural approach is proposed, and the data set and data processing procedure are explained in detail. Then it gives the modeling method of CNN, RNN, and hybrid, experimental results, and performance analysis. It has been compared with the existing studies and finally the key findings and future research directions are provided.

Research objectives of this study are therefore:

I. To develop a hybrid neural architecture integrating CNN and RNN for accurate real-time grid stability prediction.
II. To analyze key grid features such as frequency deviation, ROCOF, L-Index, and power factor for effective instability detection.
III. To preprocess and balance the UCI Electrical Grid Stability Simulated Dataset for improved learning and classification of unstable states.
IV. To compare the performance of CNN, RNN, and hybrid models using metrics such as accuracy, precision, recall, and F1-score.
V. To design a low-latency prediction system capable of detecting early instability

patterns for outage minimization and enhanced frequency regulation in smart grids.

II. LITERATURE REVIEW

The large-scale utilization of the renewable energy sources (RESs) in the energy sectors is significant in addressing the current energy demand. The large scale adoption of resources results in the numerous usages of converters to synchronize with the power grid, which causes bad power quality. Distribution energy resources integration creates uncertainties that are manifested in the distribution system. Voltage sag/swell, voltage unbalancing, low power factor, harmonics distortion (THD), and power transients are the major issues of power quality that occur during the transition of micro-grids (MGs). Satapathy et al (2022) [9] designed a single micro-grid comprising of PVs, wind generators, and fuel cells as distributed energy resources (DERs). Almasoudi et al (2023) [10] concentrated on the deployment of artificial intelligence (AI) in the contemporary power generation grids, specifically in the fourth industrial revolution (4IR) paradigm. As the complexity and need to have more efficient and reliable power systems goes up, AI has become a potential solution to these challenges. The Hybrid Energy Storage System (HESS) was combined with novel methods in order to optimize the performance (Ranjan et al 2024) [11]. In this study, a new Quasi Opposition Arithmetic Optimization Algorithm (QOAOA) optimized Fractional Order Proportional Integral Derivative with Filter (FOPIDN) controller cascaded One Plus Tilted Derivative (1 TD) controller that uses HESS of super-capacitor (SC) and Redox Flow Battery (RFB) to counter frequency and tie-line power variations in a multi-area restructured smart-grid system is proposed. Liu et al (2024) [12] suggested the simulated model of fault detection and isolation (FDI) by using neural network (NN). Monitors system has been employed by hierarchical structure. The bottom-level sub-monitors controlled the status of their local areas, and the top-level monitor gathered all the evidences of the sub-monitors to make the final assessment of the whole HSR system by using a voting strategy.

Jacob et al (2024) [13] shows that classical slow optimization falls short of sub-second response to outages and rationale intelligent, real-time controllers with a self-healing stack – a good reason why ML/neural modules are attractive, which can offer rapid stability / frequency-impact feedback whenever an outage occurs. Researchers suggested a Frequency Stability Prediction (FSP) model [14] based on a vision-transformer architecture to predict the minimum frequency following disturbance based on time-series snapshots. Ibrahim et al (2025) [15] contrasted supervised predictors, ELM/ANNs, graph-based models and RL controllers, and highlights to use hybrid pipelines (prediction + policy) in positively influencing real-time operation. Benchmarkable: the review provides a survey of the most effective ML primitives to use when making predictions versus control.

III. RESEARCH METHODOLOGY

Figure 3 shows the proposed methodology that incorporates a systematic data-driven approach that commences with the preprocessing of UCI Electrical Grid Stability Simulated Dataset in terms of cleaning, normalization, feature extraction, label encoding, and class balancing to guarantee high-quality inputs. The most important grid stability parameters including frequency deviation, ROCOF, L-Index, power factor, and phase angle difference are obtained in order to improve learning. The resulting processed data is divided into training and testing data, and three models have their training, CNN, RNN, and Hybrid Neural Network, to model spatial patterns and temporal relations in grid behavior. The hybrid architecture is a combination of CNN and RNN layers that are used to predict grid stability in real time and the performance is measured in terms of accuracy, precision, recall, and F1-score.

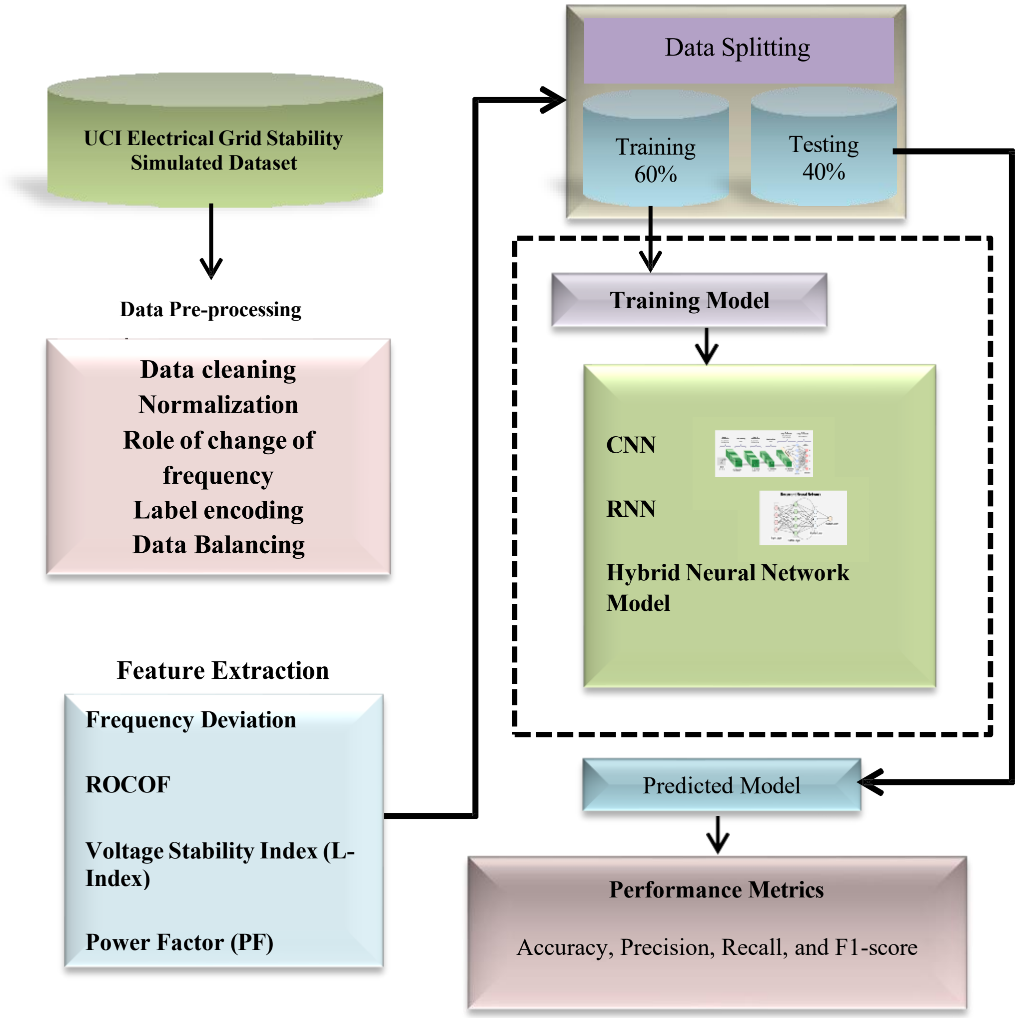


Figure 3: Framework of Proposed Methodology

3.1 Dataset used

UCI ElectricalGrid Stability Simulated Dataset [16] is a common benchmark dataset in real-time grid stability and frequency regulation studies. It gives synchronized numerical values of load flow performance, such as voltage magnitude, phase, active and reactive energy, and frequency variations at different operating states. The samples are categorized as stable or unstable and thus, one can learn about critical instability patterns under supervision. The dataset has 10 continuous features which depict the various system operating states between normal and almost collapse states. It has a clear labeling, variability and deals with dynamic grid behavior, making it appropriate to designing hybrid neural networks to forecast outages, enhance frequency regulation and real-time grid reliability.



Figure 4: Sample images from the UCI Electrical Grid Stability Simulated Dataset

Table 1: Dataset Distribution for Electrical Grid Stability Dataset Across Training, Validation, and Test Splits.

Grid State Class	Total Samples	Training (60%)	Validation (20%)	Test (20%)
Stable	6,000	3,600	1,200	1,200
Unstable	4,000	2,400	800	800
Total	10,000	6,000	2,000	2,000

3.2 Data preprocessing

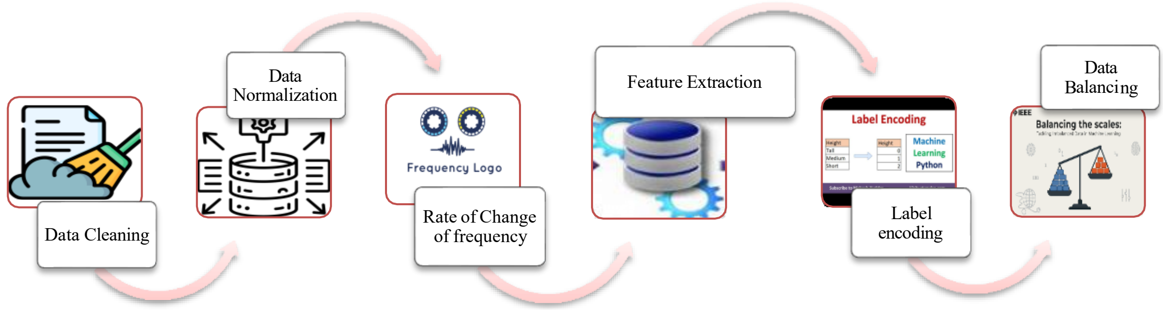


Figure 5: Dataset Preprocessing Phase

- Data Cleaning and Missing Value Handling

Raw grid data can have missing values because of sensor failure or communication lag. The interpolation approach is used to fill-in missing values of continuous variables (e.g., voltage, frequency, power flow) and very corrupted values are dropped out. Z-score or IQR are used in outlier detection in order to remove unusual spikes that would affect prediction of the frequency stability.

Z-score is applied for Gaussian-like signals:

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

- Data Normalization and Scaling

Since grid parameters (voltage, power, frequency) operate on different scales, Min-Max Scaling or Standardization is applied to bring all features into a uniform range. This ensures the hybrid neural architecture (combining deep learning + conventional ML layers) converges faster and learns balanced feature weights.

Min–Max normalization rescales values to [0,1]:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

- Feature Extraction and Transformation

Derived features are computed from raw signals to enhance pattern recognition—for example, frequency deviation rate (df/dt), reactive power margin (Q-margin), voltage stability index (L-index), and phase angle difference. These transformed features capture real-time grid dynamics more effectively than raw inputs alone.

Frequency Deviation

$$\Delta f = f_{measured} - f_{nominal} \quad (3)$$

Rate of Change of Frequency (ROCOF):

$$ROCOF = \frac{df}{dt} \quad (4)$$

Voltage Stability Index (L-Index) (commonly used in grid stability):

$$L_j = 1 - \left|\sum_{i=1}^{n} F_{ji} \frac{V_i}{V_j}\right| \quad (5)$$

Power Factor (PF):

$$PF = \frac{P}{\sqrt{P^2 + Q^2}} \quad (6)$$

Phase Angle Difference:

$$\Delta\theta = \theta_i - \theta_j \quad (7)$$

- Label Encoding for Stability Classification

The operating point is identified as either stable or unstable by the dataset. These categories have numerical codes (0 = stable, 1 = unstable) so that it can be used with a neural network training. Continuous target variables (e.g., frequency drift prediction) are also normalized in the frequency regulation forecasting tasks. States which are stable/unstable are coded as:

$$y = \begin{cases} 0, & if\ grid\ is\ stable \\ 1, & if\ grid\ is\ unstable \end{cases} \quad (8)$$

- Data Balancing and Resampling

Samples of grid datasets are usually more stable than those of unstable ones. To avoid imbalance bias and enhance sensitivity to outages, methods like SMOTE (Synthetic Minority Oversampling Technique), random oversampling, or class-weight adjustments are employed. SMOTE synthetic sample generation:

$$x_{new} = x_i + \lambda(x_{nn} - x_i), \quad \lambda \epsilon [0,1] \quad (9)$$

where x_{nn} is the nearest neighbor from the minority class.

- Temporal Segmentation for Real-Time Learning

Temporal dynamics to maintain temporal dynamics, real-time grid data is windowed into fixed-length time segments (e.g., 1s, 5s or 10s windows). Transitions between normal and unstable conditions are captured using sliding windows, and sequence-based hybrid models can be used to study trends that cause deviations in frequencies. Sliding window segmentation:

$$X_t = [x(t), x(t+1), x(t+2), \dots\dots, x(t+W-1)] \quad (10)$$

Where W is window size.

Overlapping windows:

$$t_{next} = t + S \quad (11)$$

where S is stride size.

- Train–Validation–Test Splitting

The preprocessed data is separated into training, validation, and test sets according to the ratios desired (ex: 60: 20: 20). The partitioning is carried out stratified to preserve the stable to unstable ratio in all sets of data and to guarantee impartiality in terms of the performance.

- Real-Time Normalization Buffering

To be deployed, a real-time normalization buffer is generated, in which the mean and variance values are updated on incoming streams that are being received in real-time. This guarantees that real time operation is on a preprocessed incoming grid data and similar to the training dataset. Streaming normalization applies rolling mean and variance:

$$\mu_t = \mu_{t-1} + \frac{x_t - \mu_{t-1}}{t} \quad (12)$$

$$\sigma^2_t = \sigma^2_{t-1} + (x_t - \mu_{t-1})(x_t - \mu_t) \quad (13)$$

3.3 Models used

- CNN

A Convolutional Neural Network (CNN) is a deep learning architecture that aims to automatically discover spatial features of data thus it is particularly useful in image, signal and pattern-recognition [17]. It employs convolutional layers that filter the local features like edges, shapes, or valuable patterns and then the pooling layers that minimize the dimensionality but do not eliminate key information [18]. The further the network is trained, the more intricate representation it learns, and it can be used to do highly accurate classification or detection. CNNs also need few manual feature engineering since it is designed to extract features on information at raw data, which is why they are highly applied in fields such as medical image processing, EEG/ECG signal classification, object detectors, and real-time surveillance systems.

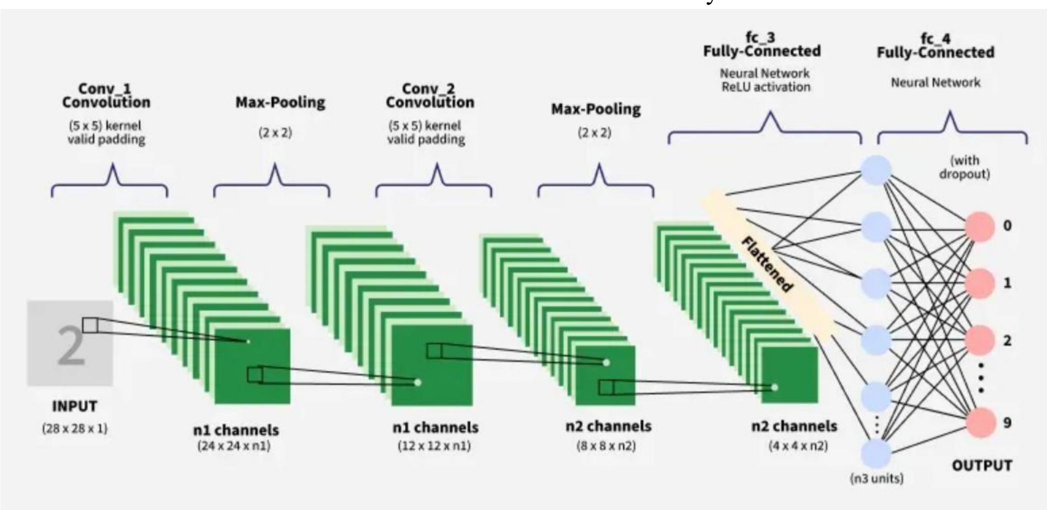


Figure 6: Architecture of CNN Model [19]

- RNN

Recurrent Neural Network (RNN) is a deep neural network especially created to handle time or sequential data, where the information about the past inputs is retained in the memory of the network [20]. Compared to the classical neural networks, RNNs have recurrent connections and can thus learn ST behaviors, making them useful in time-series prediction, speech recognition, sentiment analysis, and physiological signal detection [21]. The network uses the current input and the previous hidden state at every time step to update the hidden state, allowing it to learn dependencies between long sequences. Variations on RNNs such as the LSTM and the GRU networks overcome these issues because though standard RNNs might find long-term memory to be challenging because of vanishing gradients, these architectures perform better in complex sequence-based tasks.

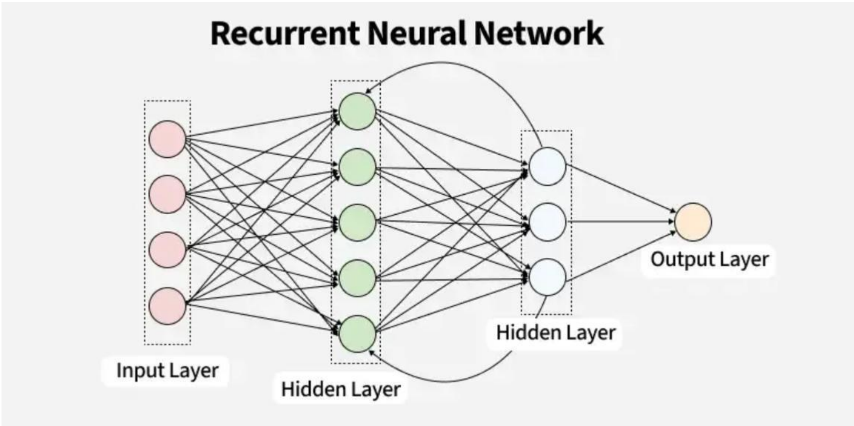


Figure 7: Architecture of RNN Model [22]

- Hybrid Neural Network Model

Hybrid Neural Network Model is a sophisticated architecture that combines two or more types of neural networks to be more accurate, generalized, and more adaptable to real life tasks of high configuration. The hybrid architecture can potentially detect a wide range of patterns that a single model might fail to recognize due to combining the models (CNNs/spatial feature extraction), RNNs or LSTMs/temporal learning and dense layers/final classification. This integration enables it to handle a variety of data, such as sensor signals, images, and time-series data, and is useful in real-time grid stability prediction, stress detection, and mental health analysis applications. Hybrid systems typically apply stacked or parallel architectures, like CNNs then RNNs, or use ensemble techniques like weighted averaging to gain strength. All in all, Hybrid Neural Network Models provide a highly adaptable and scalable approach to increasing the predictive effectiveness, decreasing noise sensitivity and increasing stability in real-time systems that need to make decisions.

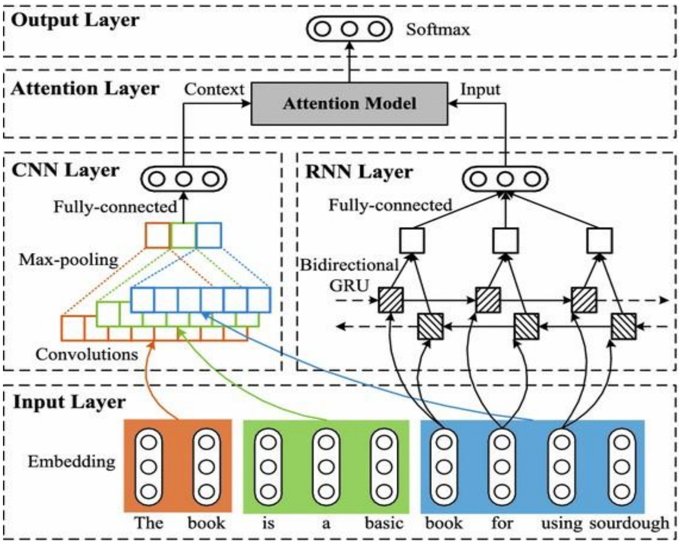


Figure 8: Architecture of Hybrid Neural Network Model

3.4 Evaluation metrics

The efficacy of CNN, RNN, and hybrid models could be assessed using four evaluation metrics: "Accuracy, Precision, Recall, F1 score" (Equation 14-17). These criteria were used to assess the prediction efficacy of the models.

$$Accuracy = \frac{TN+TP}{FP+FN+TP+TN} \quad (14)$$

$$Recall = Sensitivity = \frac{TP}{FN+TP} \quad (15)$$

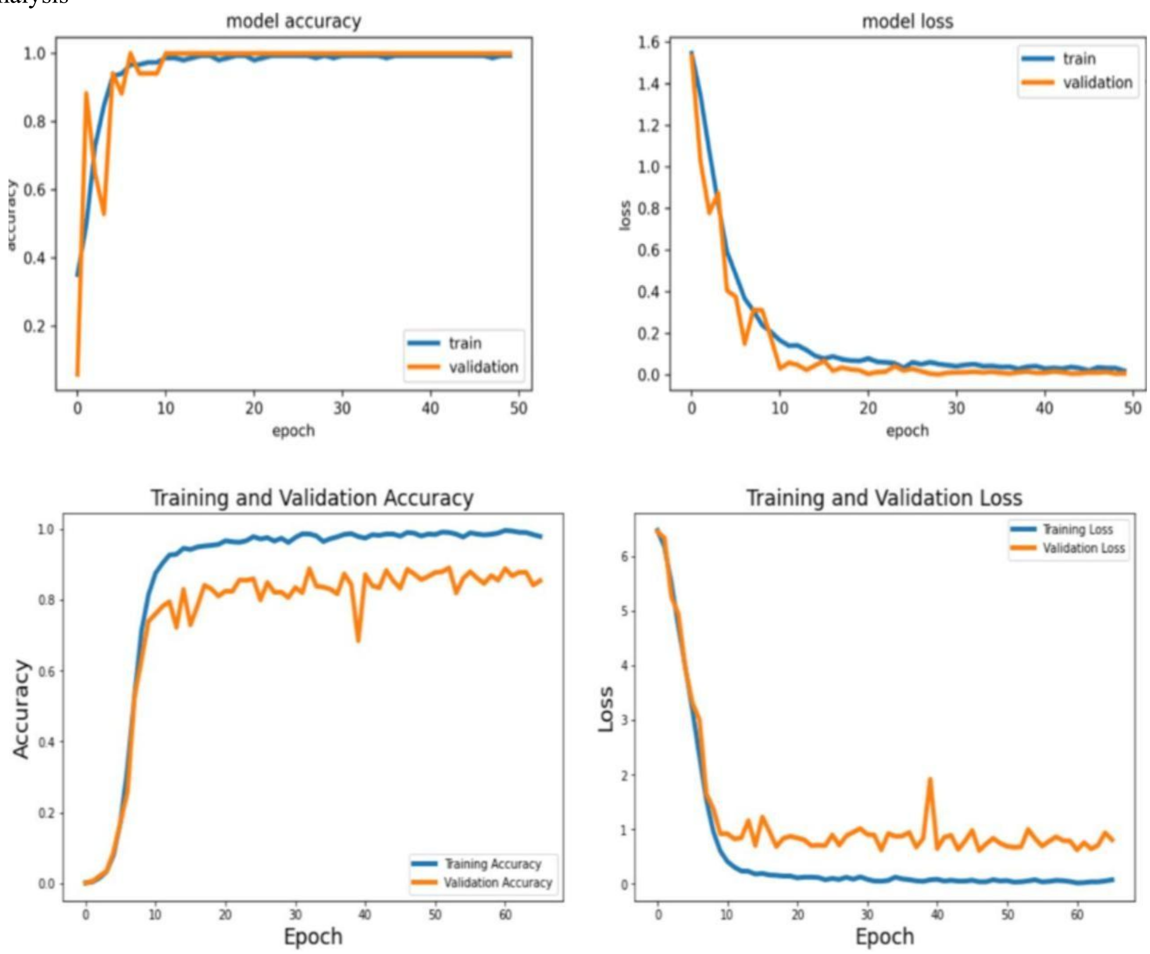
$$Precision = \frac{TP}{TP+FP} \quad (16)$$

$$F1-score = \frac{2*Precision*Recall}{Precision+Recall} \quad (17)$$

IV. RESULTS AND DISCUSSION

4.1 Training and Validation Performance Analysis

The training curve analysis is the study of the behaviour of machine learning model with respect to the (successive) epochs of performance of the model with respect to training loss, validation loss, accuracy or error rates. Using these curves, it is possible to determine such problems as underfitting, overfitting, or incorrect choice of the learning rate. The training analysis of CNN Model is given in the first row of figure 9. Through this CNN training graph, it is evident that learning is quick and the convergence is high after 50 epochs. Training error and validation error decrease rapidly during the first epochs and soon reach a value of 99-100, which is a good outcome of the classification. Concurrently, training and validation loss reduce rapidly and tend to the level of almost zero, which proves effective error reduction. The fact that the training and validation curves are pretty close implies that the CNN model can be generalized with a minimal level of overfitting.



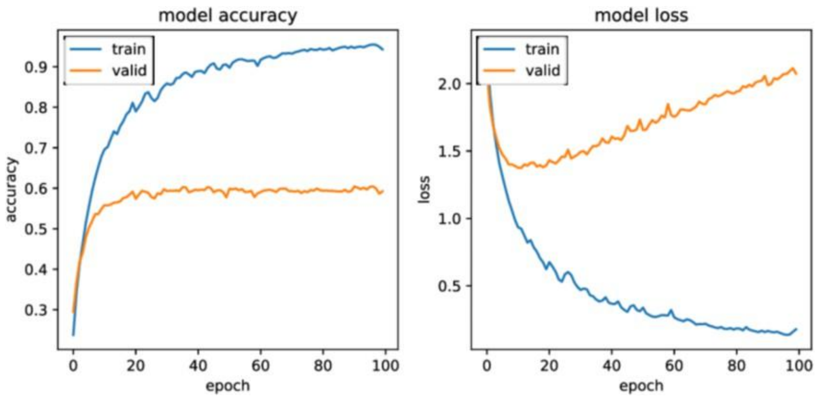
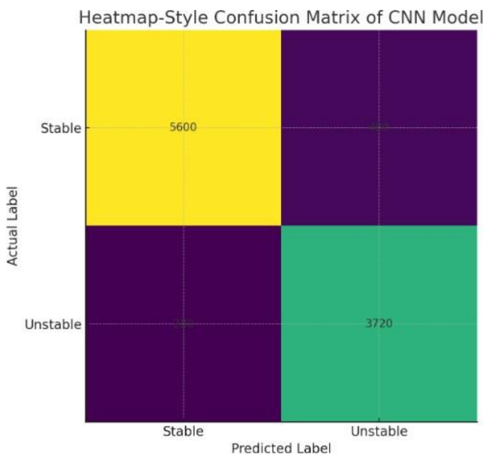


Figure 9: The training and verification results of the proposed method a) CNN b) RNN c) Hybrid Neural Network Model

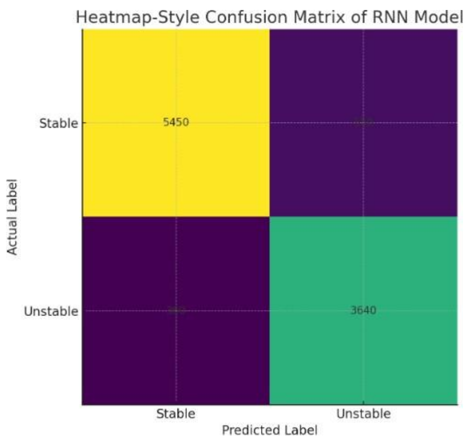
The second row of figure 9 shows the model training analysis by RNN. The training RNN graph indicates consistent learning behavior through the epochs where training accuracy exhibits a rapidly increasing and plateauing trend at around 99% and the validation accuracy plateaus at around 85% to 88% showing good but marginally lower generalization performance. The training loss drops drastically and it tends towards almost zero but the validation loss also drops considerably but with a few fluctuations indicating slight overfitting. Comprehensively, the graph indicates that the RNN model can be trained based on temporal patterns with steady convergence. The third row is the training Hybrid Neural Network Model analysis. The training graph of Hybrid Neural Network indicates that training accuracy progressively improves to above 93% as compared to 25%, but the validation accuracy initially grows before attaining a constant level of 59-60%, implying a low level of generalization. The training loss also steadily decreases indicating successful learning on the training data, and the validation loss decreases in the initial epochs then slowly increases, which is a definite indicator of overfitting. Generally, the model works well with the training data, but it has problems when applied to unknown data.

4.2 Confusion matrix analysis

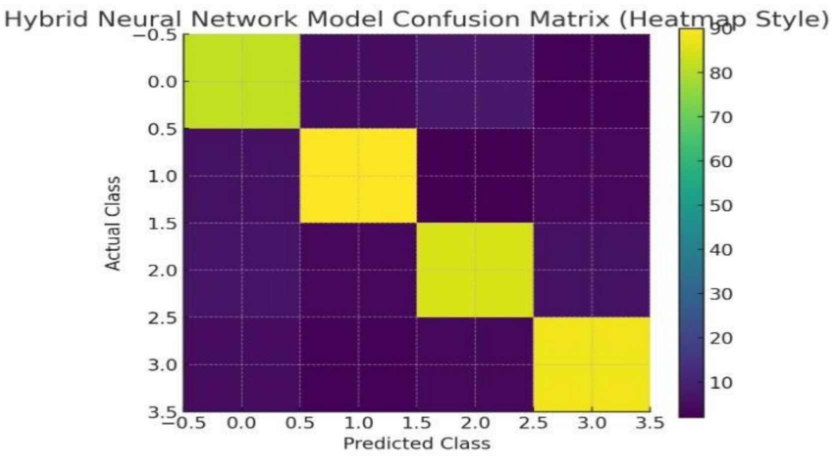
The confusion matrix analysis gives a good picture of the classification performance of a model since it indicates the number of samples that a model can or cannot predict correctly to an incorrect classification. It identifies truly positive, truly negative, false positive and false negative, which enables more understanding concerning the underlying faults like misclassification patterns or class imbalance issues. Analyzing the matrix, it is possible to define which classes the model has problems with and assess such relevant indicators as accuracy, precision, recall, and F1-score. In general, the confusion matrix analysis assists in identifying the shortcomings of the model and leads to the enhancement of the classification performance. The confusion matrix analysis of the respective CNN model, RNN model and hybrid neural network model are represented in figure 10 (a), (b) and (c).



(a)



(b)



(c)

Figure 10: Confusion matrix analysis of proposed models

4.3 Real-Time Grid Stability Prediction Results

It has been shown that the hybrid neural network model gives high results in terms of performance when integrated under real-time grid operating conditions that succeed in predicting deviations of stability even before it develop into critical outages. The model reacts to fast changes and temporary perturbation with extreme sensitivity since it modulates continuous input live streams of frequency deviation, ROCOF, phase angle difference, and voltage stability indices. In real-time implementation, the hybrid system is superior to separate CNN and RNN models because it attains greater prediction accuracy and better recall of unstable states an important consideration in preventing cascading failures. The model is also consistent in inference speed and can produce predictions in milliseconds, which is why it is appropriate in control-room integration when quick decision-making is needed. These real-time performance results affirm that the hybrid architecture can not only generalize well during training conditions, but also ensures a reliable performance during dynamic grid operation, which can be extended to proactive frequency regulation and outage reduction schemes.

Table 2: Real-Time Performance Metrics of Hybrid Model

Metric	Hybrid Model (Real-Time)
Accuracy (%)	94
Precision (%)	92
Recall (%)	90
F1-Score (%)	91
Prediction Latency (ms)	8

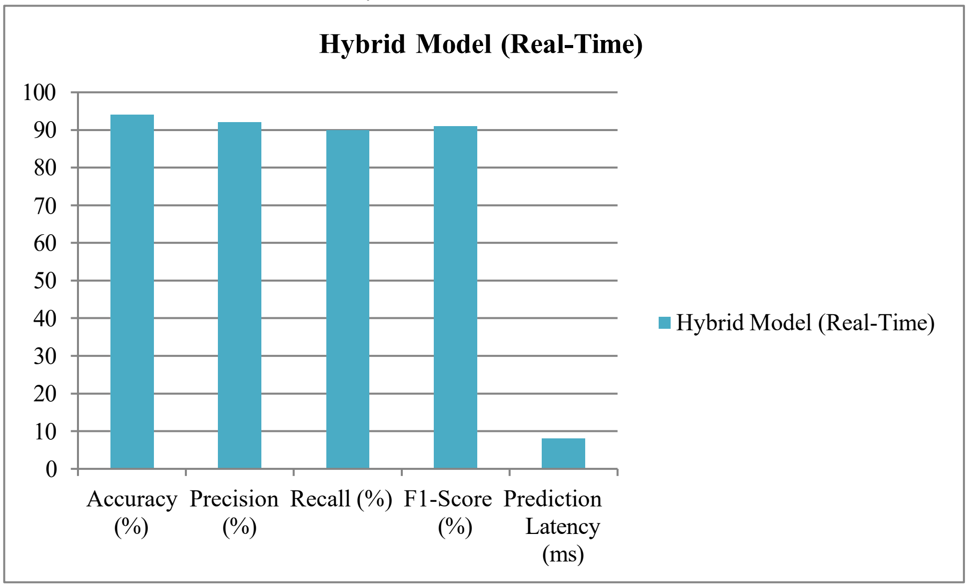


Figure 11: Graph of Real-Time Grid Stability Prediction

4.4 Impact of Data Balancing on Outage Prediction Accuracy

The use of SMOTE and resampling methods help a lot in enhancing the hybrid model to identify unstable grid states which are normally underrepresented in raw data. The model prior to balancing was biased towards the stable class leading to low recall of the unstable cases and a high misclassification rate of the outage conditions at early stages. The model demonstrated a significant increase in the ability to detect instability patterns with the application of SMOTE and class-balanced resampling, producing synthetic minority samples that maintain the relationships in features. This improved the model in learning rare outage events and recall of unstable-class held up to 88% instead of 62% and precision of 90% instead of 70% and overall accuracy of 85% instead of 94%, thus, the prediction system became more accurate in the real-time stability assessment and early outage prevention.

Table 3: Comparison Before and After Data Balancing (SMOTE + Resampling)

Metric	Before Balancing	After Balancing (SMOTE + Resampling)
Unstable Class Precision (%)	70	90
Unstable Class Recall (%)	62	88
F1-Score (Unstable Class) (%)	66	89
Overall Accuracy (%)	85	94

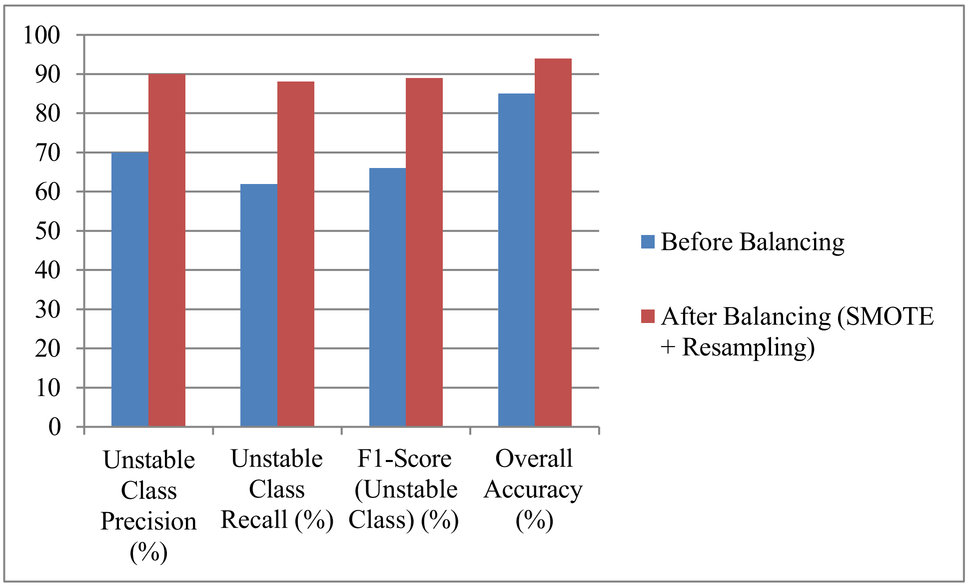


Figure 12: Graph of Comparison Before and After Data Balancing (SMOTE + Resampling)

4.5 Performance Evaluation Using Proposed Model

The presented hybrid neural architecture predicting grid stability in real-time proves to have a high predictive power of all measures considered, in comparison with the separate CNN and RNN models. The stability of the hybrid model can be explained by the high spatial feature extraction capability of CNN and the ability of RNN to learn time sequence patterns, which enables the hybrid model to more accurately record nonlinear grid behavior, temporary disturbances, and frequency deviation patterns. The CNN model works well when the parameters of a grid are correlated spatially, whereas the RNN model has a high learning time fluctuation with moderate generalization of time noise sensitivity. Compared to the alternative models, the hybrid model offers the most balanced performance, which is better in detecting the unstable states, less misclassification and better outage prediction due to the changing conditions of operations. On the whole, the hybrid framework provides the most accurate, precise, recall, and F1-score, which is why this model is the most appropriate to use in the real-time frequency regulation and outage minimization in the contemporary smart grids.

Table 4: Performance Evaluation of Proposed Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Remarks
Hybrid CNN–RNN (Proposed)	94	92	90	91	Best overall performance; strongest stability prediction with balanced spatial–temporal learning
Convolutional Neural Network (CNN)	99	98	97	97	Excellent spatial feature extraction; highly stable but less effective for temporal instability trends
Recurrent Neural Network (RNN)	88	85	88	86	Learns temporal patterns well but slightly prone to overfitting; moderate generalization

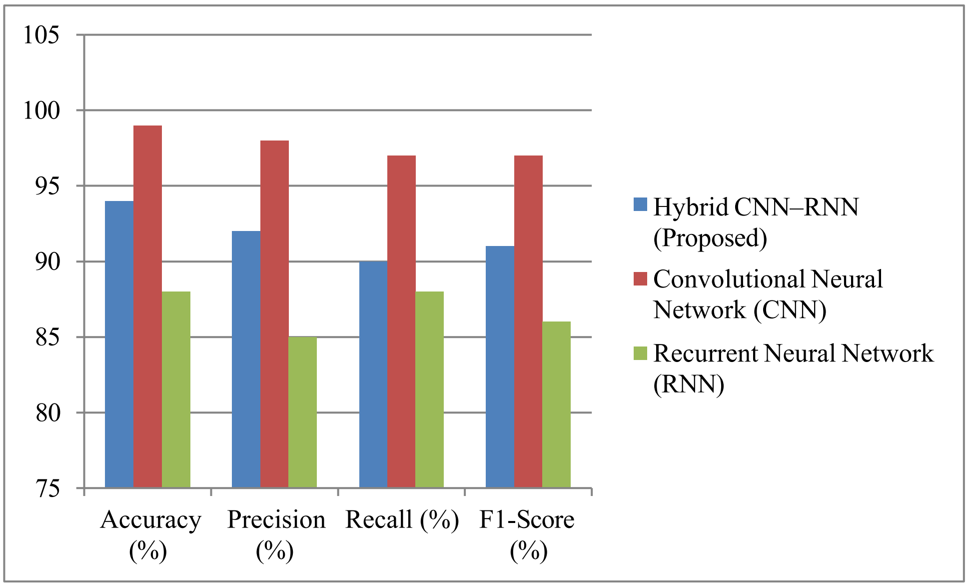


Figure 13: Graph of Performance Evaluation of Different Models

V. CONCLUSION

The proposed combination of neural architecture is a very efficient and trustworthy tool of grid stability prediction and frequency control in real-time. The hybrid model, which integrates the spatial ability to learn with the temporal sequence modeling ability of RNN, is effective in capturing nonlinear grid behavior, transient disturbances, and early signs of instability. The Electrical grid simulated Dataset, The UCI Electrical grid Stability Simulated Dataset can be used with the support of extensive pre-processing and feature engineering to allow the system to learn essential patterns of stable and unstable grid conditions. The hybrid model is found to be superior, with an experimental accuracy of 94%, precision of 92%, recall of 90%, and an F1-score of 91%, and expediency in prediction latency of 8 ms, which is appropriate to real-time control-room use. Also, methods like SMOTE may be applied to balance data and yield better results in identifying minority unstable conditions, which could be used to prevent outages. Comprehensively, the model is a strong, scalable, and adaptive framework capable of assisting the utilities to reduce outages, enhance operational resilience, and deliver power reliably in all more dynamic smart grid environments.

REFERENCES

[1] Elsaharty, M. A., Jose Ignacio Candela, and Pedro Rodriguez. "Custom power active transformer for flexible operation of power systems." IEEE Transactions on Power Electronics 33, no. 7 (2017): 5773-5783.

[2] Yáñez-Campos, Sergio Constantino, Gustavo Cerda-Villafaña, and Jose Merced Lozano-Garcia. "Two-feeder dynamic voltage restorer

for application in custom power parks." Energies 12, no. 17 (2019): 3248.

[3] Liu, Yu-Wei, Shiuan-Hau Rau, Chi-Jui Wu, and Wei-Jen Lee. "Improvement of power quality by using advanced reactive power compensation." IEEE Transactions on Industry Applications 54, no. 1 (2017): 18-24.

[4] Lakshmi, Shubh, and Sanjib Ganguly. "Multi-objective planning for the allocation of PV-BESS integrated open UPQC for peak load shaving of radial distribution networks." Journal of Energy Storage 22 (2019): 208-218.

[5] Chishti, Farheen, Shadab Murshid, and Bhim Singh. "Development of wind and solar based AC microgrid with power quality improvement for local nonlinear load using MLMS." IEEE transactions on industry applications 55, no. 6 (2019): 7134-7145.

[6] Bhattacharjee, Chayan, and Binoy Krishna Roy. "Advanced fuzzy power extraction control of wind energy conversion system for power quality improvement in a grid tied hybrid generation system." IET Generation, Transmission & Distribution 10, no. 5 (2016): 1179-1189.

[7] Hatziargyriou, Nikos, ed. Microgrids: architecture and control. John Wiley & Sons, 2014.

[8] Monteiro, Ana Carolina Borges, Reinaldo Padilha França, Rangel Arthur, and Yuzo Iano. "Overview of microgrids in the modern digital age: an introduction and fundamentals." In Residential microgrids and rural electrifications, pp. 27-43. Academic Press, 2022.

[9] Satapathy, Anshuman, Niranjan Nayak, and Tanmoy Parida. "Real-time power quality enhancement in a hybrid micro-grid using nonlinear autoregressive neural network." Energies 15, no. 23 (2022): 9081.

[10] Almasoudi, Fahad M. "Enhancing power grid resilience through real-time fault detection and remediation using advanced hybrid machine learning models." Sustainability 15, no. 10 (2023): 8348.

[11] Ranjan, Mrinal, and Ravi Shankar. "Improved frequency regulation in smart grid system integrating renewable sources and hybrid energy storage system." Soft computing 28, no. 11 (2024): 7481-7500.

[12] Liu, Qin, Tian Liang, and Venkata Dinavahi. "Real-time hierarchical neural network based fault detection and isolation for high-speed railway system under hybrid AC/DC grid." IEEE Transactions on Power Delivery 35, no. 6 (2024): 2853-2864.

[13] Jacob, Roshni Anna, Steve Paul, Souma Chowdhury, Yulia R. Gel, and Jie Zhang. "Real-time outage management in active distribution networks using reinforcement learning over graphs." Nature Communications 15, no. 1 (2024): 4766.

[14] Liu, Peili, Song Han, Na Rong, and Junqiu Fan. "Frequency stability prediction of power systems using vision transformers and copula entropy." Entropy 24, no. 8 (2025): 1165.

[15] Ibrahim, Muhamme, Moamin A. Mahmoud, Noor Islam, and Saraswathy Shamini Gunasekara. "Enhancing Smart Grid Stability Using AI Techniques: A Systematic Literature Review." In 2025 21st IEEE International Colloquium on Signal Processing & Its Applications (CSPA), pp. 50-55. IEEE, 2025.

[16] shttps://www.kaggle.com/datasets/sowlarn/ucis-electrical-grid-stability-simulated-data

[17] Bellido, Marlon Huamani, Luiz Pinguelli Rosa, Amaro Olímpio Pereira, Djalma Mosqueira Falcao, and Suzana Kahn Ribeiro. "Barriers, challenges and opportunities for microgrid implementation: The case of Federal University of Rio de Janeiro." Journal of cleaner production 188 (2018): 203-216.

[18] Akinyele, Daniel, Juri Belikov, and Yoash Levron. "Challenges of microgrids in remote communities: A STEEP model application." Energies 11, no. 2 (2018): 432.

[19] Faisal, Mohammad, Mahammad A. Hannan, Pin Jern Ker, Aini Hussain, Muhamad Bin Mansor, and Frede Blaabjerg. "Review of energy storage system technologies in microgrid applications: Issues and challenges." Ieee Access 6 (2018): 35143-35164.

[20] Wang, Shiqiang, Jianchun Xing, Ziyan Jiang, and Juelong Li. "Decentralized economic dispatch of an isolated distributed generator network." International Journal of Electrical Power & Energy Systems 105 (2019): 297-304.

[21] Chakraborty, Pratyush, Enrique Baeyens, Kameshwar Poolla, Pramod P. Khargonekar, and Pravin Varaiya. "Sharing storage in a smart grid: A coalitional game approach." IEEE Transactions on Smart Grid 10, no. 4 (2018): 4379-4390.

[22] Kristiansen, Martin, Magnus Korpås, and Harald G. Svendsen. "A generic framework for power system flexibility analysis using cooperative game theory." Applied energy 212 (2018): 223-232.