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# Predictive Load Balancing and Fault-Tolerant Control in Decentralized Nano-Grid Systems through AI-Enhanced Hybrid CNN-GRU Model

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## Highlights of the Study

- Proposed a Hybrid CNN-GRU Model that integrates spatial feature extraction with temporal sequence learning for accurate load forecasting and real-time fault classification in decentralized nano-grid systems.
- Achieved High Predictive Accuracy, with a load forecasting MAPE of just 3.14% and fault classification accuracy of 96.94%, significantly outperforming traditional and deep learning baselines.
- Enabled Real-Time Control with Low Latency, maintaining inference times under 15 ms and fault response actions within 500ms, ensuring suitability for edge deployment in resource-constrained environments.
- Demonstrated Enhanced Energy Efficiency, improving utilization rates by up to 20% across diverse grid scenarios through intelligent, predictive load balancing and fault-tolerant decision-making.

## Abstract

The increasing integration of renewable energy sources in decentralized nano-grid systems presents new challenges in maintaining load balance and ensuring fault resilience due to the intermittent and nonlinear nature of energy flows. In this paper, we introduce a hybrid CNN-GRU architecture integrated with AI that exploits the advantages of both Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) in a time-sensitive energy management context within nano-grid environments. The model is trained on the room temperature in the earliest conversations, using high resolution time-series measurements obtained by smart meters and energy nodes, specifically the parameters of voltage, current, frequency, and state-of-charge ( SoC ). The proposed model outperformed conventional methods like ARIMA, Random Forest and LSTM, standalone CNN and GRU in terms of accuracy and Mean Absolute Percentage Error of forecasting load (3.14%) and fault classification (96.94%) having conducted the large-scale experimentation. In addition, the model attained low inference latency of less than 15 milliseconds and has a fault response time of less than 500 milliseconds, which confirmed that it was applicable in edge deployment. Experimentations in the real world demonstrated an energy consumption reduction of up to 20% in different operating conditions related to peak demand, renewable surplus, and grid failure. In our research, we show that by integrating deep learning with edge-intelligent control it is possible to greatly increase the resilience, adaptability and sustainability of the next generation decentralized power systems. CNN-GRU can be a good use case as the prediction engine in the sense of short-term load balance and real-time fault recovery, and the model may be useful in developing smart energy infrastructure.

**Keywords-**Nano-Grid, Load Forecasting, Fault Detection, CNN-GRU, Hybrid Deep Learning, Energy Efficiency, Decentralized Grid, Predictive Control.

## 1. Introduction

Due to the increased worldwide focus on eco-friendly power consumption and the decentralization of electrification, nano-grids have become the potential way to accommodate renewable energy supply at the community or building scale. A nano-grid is a localized, small-scale grid system that can be operated in both a grid connected and an islanded mode, and usually consists of renewable energy sources (e.g. solar PVs, wind turbines), energy storage systems (ESS), smart loads, and microcontrollers [1] [2]. Such systems provide greater flexibility that enables their own power management, which improves the energy accessibility, as well as reliability and the sustainability of the environment. Nevertheless, in as much as nano-grid systems have their virtues, they have come at complex operational problems. The large storage inconsistency and load-generation imbalance caused by the intermittent generation of the renewables results in instability of voltage/frequency [3] [4]. Furthermore, energy resources are limited, and centralised control is not an option, which means that it is not possible to detect faults or optimise energy in real time. This demands smart models that can predict the short-term energy demand, detect fault patterns in advance and play corrective measures in real-time, thus serving the purpose of sustainable power delivery without any breaks [5] [6].Figure 1 illustrates key components involved in load balancing and fault-tolerant control within decentralized nano-grid systems.

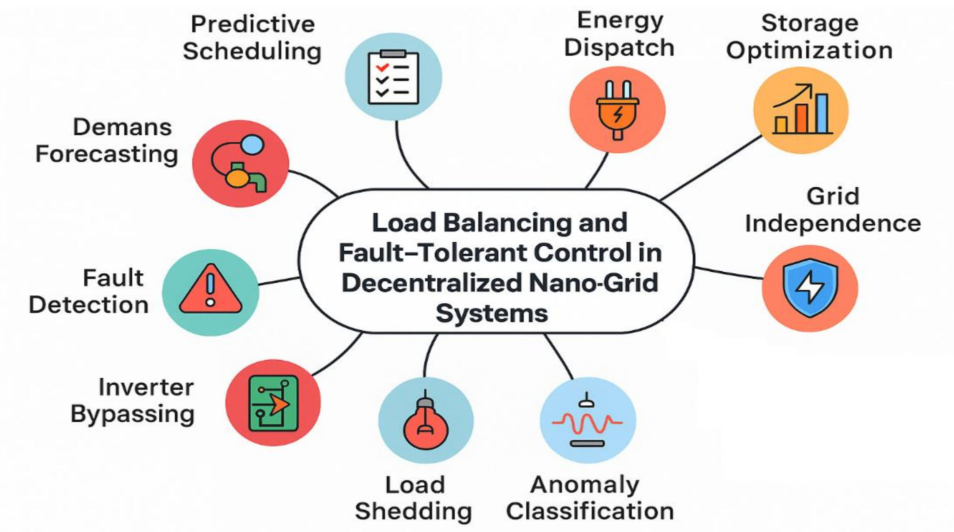


**Figure 1. Load Balancing and Fault Control**

Traditionally, statistical results and rule-based technology had been used in energy forecasting and fault detection in the grid systems. Load prediction has considerably been done using time-series forecasting methods like Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA) and Holt-Winters models. Although the models can operate under linear and stationary assumptions, it is difficult to find those that can model the nonlinearities and sharp changes that a nano-grid usually displays [7] [8]. The modeling of temporal sequences has become a popular subject of interest of deep learning models, especially Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs). LSTM has proved to be efficient when it comes to load predictions but the GRUs provide a simpler method with a similar level of accuracy and with fewer demanding calculations.

A number of hybrid models have been suggested including LSTM-CNN, CNN-LSTM, and DenseNet-RNN hybrids. These hybrids advance the performance of single architectures, being however, complex, computationally costly, and sometimes uninterpretable. Also, the real-time forecast of the load and subsequent fault detection have often been considered separately with few works that combine the two in an integrated solution that can make the decisions and control simultaneously [9] [10]. In order to face the above CHs, this work presents a new hybrid AI model, namely, the AI-Enhanced Hybrid CNN-GRU Model. The model is specifically made to be used in the real-time, edge-limited nano-grid applications, where predictions made need to be quick and precise. CNN component extracts the spatial interdependencies in the sensor features, including voltage, current and frequency whereas GRU component learns both long and short-term temporal dependencies in energy sequences. The integration enables the model to predict load highly accurately and identifies fault events in very less time.

## 1.1 Research Motivation

The proposed research is driven by the fact that improving the stability, and reliability of the decentralized nano-grid systems in crucial medical environments like the rural clinics and emergency facilities is a rather timely need. These lookout settings make use of more off grid renewable energy which is not only intermittent but also unreliable. A model based on AI that can support real-time load prediction and fast recovery of fault is necessary to combat life-threatening breakdowns of the essential medical equipment. The present study fulfils that requirement by employing a hybrid deep learning based control technique.

## 1.2 Significance of the Study

The study has value to the development of the decentralized energy systems due to the rapid changes toward renewable energy across the globe. As more homes and businesses in smart cities, rural electrification, and industrial microgrids become nano-grid systems, they have to be smarter and more resilient. The study proposes a hybrid framework of CNN-GRU, which integrates predictive load balancing and fault detection by empowering them to react autonomously in real time. Its low-footprint in computing resources and scalability capabilities make the model fit to be deployed in the edge and pave the way to the next-generation smart grids, EV infrastructure, and disaster-resilient energy networks that can provide sustainable as well as self-controlled power systems.

## 1.3 Problem Statement

Decentralized nano-grid systems experience various issues, which act against the efficiency of operation. The volatile nature of energy generators such as solar and wind energy makes them unpredictable, therefore, leading to load-generation mismatches. The traditional models cannot capture spatial-temporal dependency of real-time data and forecast poor and inefficient energy dispatch. Moreover, overlapping failure signatures make fault identification hard because conventional systems fail to classify them into specific categories. The current connection and practice to address the issues of load forecasting and fault detection are separate. This paper fills those gaps by suggesting a coherent AI-based CNN-GRU solution that will simultaneously forecast, fault categorization, and provide real-time control in edge-limited nano-grid settings.

### 1.4 Recent Innovations and Challenges

Latest advances in intelligent energy systems involve LSTM-based forecasting, federation learning, and convolutional fault detection architectures. Equipped with edge-AI and neural networks that can now be deployed on microcontrollers, decentralized control is now supported. But there are still major issues such that deep learning models tend to be combatively opaque, making them difficult to trust in safety-critical applications, and hybrid models have high computational overheads, and therefore cannot always be run on an edge device. Also, spatial and temporal learning are not processed efficiently when they are separated in treatment. These problems become worse as sensors become more complicated and require quick reaction. The research tackles them using an a priori unified and lightweight structure, essentially CNN-GRU, which is able to infer the resilience of nano-grid in real-time back in spatiotemporal terms.

### 1.5 Key Contribution of the study

- Development of a Hybrid CNN-GRU Architecture: Proposed a new framework in deep learning which integrates Convolutional Neural Networks (CNNs) to learn spatial features and Gated Recurrent Units (GRU) to learn the temporal sequences to ensure strong spatiotemporal learning in switching energy data on a nano-grid.
- Unified Framework for Load Forecasting and Fault Classification: Developed a more integrated model that could carry out both the predictive load balancing and the real-time fault classification in a concise deep learning pipeline.
- Edge-Compatible Model Design: Prepared the proposed architecture to deploy in edge computing by processing low computational overhead and low memory usage and fast inference of an embedded system.
- Incorporation of Real-Time Control Logic: Combined AI model with real time load dispatch logic, real time fault mitigation logic, which caused the automatic user controlled decisions and automatic execution of control solutions without any external human intervention.
- Temporal Windowing and Feature Engineering Strategy: Used a regularized temporal windowing strategy and computed higher order energy indicators (e.g., the index of power deviation, frequency drift, net load slope) to endow model input with indicators of prediction.

### 1.6 Rest of Section of the Study

The structure of this study is organized to comprehensively address the research objectives. Section 2 provides an in-depth review of related studies concerning load forecasting, fault detection, and AI integration in decentralized energy systems, identifying the strengths and limitations of existing models. Section 3 details the proposed hybrid CNN-GRU methodology, including data acquisition, preprocessing, model architecture, and real-time deployment mechanisms. Section 4 describes the experimental results and discussion, highlighting model performance, energy efficiency gains, and system responsiveness across scenarios. Finally, Section 5 presents the conclusion and outlines future research directions to enhance scalability, security, and adaptive control in nano-grid applications.

## 2. Related Works

Federated Secure Dynamic Optimization Framework (FSDOF), a new method was proposed to strengthen energy management as well as resilience of smart nano grids. FSDOF provides the solution to the real-time flexibility, energy wastage, computation delay, and cybersecurity risks embedded in Digital Twin (DT) control and Multiagent Reinforcement Learning (MARL). Among them, there is the Federated Deep Model Predictive Control (FD-MPC), SecureGraph-FedNet (SG-FedNet), and the Dynamic Stochastic Neuro-Evolution Optimizer (DSNEO). DC voltage stabilization of the system was gained very quickly at 80V in less than 0.5 sec with a low Bit Error Rate (BER) at 0.012[11]. SG-FedNet that relies on Autoencoders and Graph Neural Networks had a security rate of 0.99.

The paper contains a thorough overview of hybrid nanogrid energy management systems, the discussion is conducted on the application of the said system in embedded systems that have low amount of energy reserves and extended periods of isolation concerning external power utilities. Whereas energy management is a well-developed area under buildings, EVs, and naval transport, embedded nanogrids have specific limitations poorly examined[12]. The paper contrasts hybrid nanogrids and microgrids, and they all elaborate on the components, type of operation, types of optimization and practical applications. It also points out some major hurdle and where the future research and development may look to the presence of hybrid nano grid in progressive aspect of energy efficiency, reduction of carbon footprint as well as reliable power and hence essentiality in next gen embedded energy solutions.

Microgrids have become a trend in distribution of reliable and sustainable energy, and they are affected by regulatory and market impediments in their usage. The smaller scale systems or nanogrid have additional challenges like high capital expenditure, which has to match locally generated energy demands. This paper presents a model of economic feasibility analysis that would be implemented in a nanogrid project that is being developed in Brazil, specifically to park electric vehicles[13]. Monte Carlo simulations and the method of open DSS system operation are included in the model in order to perform uncertainty analysis. It also analyses net-metering energy trades and examines the effects of policy incentives on economic viability, providing an insight into the scaling of nanogrid use in emerging energy markets.

Increasing sophistication of contemporary renewable energy and fuel systems has prompted both industrial and academic

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innovation. These need complex architectures, testing and control strategy to manage. In this work, a new multi-agent AI-driven smart control AI is suggested to maximize the utilization of power in buildings powered by renewable energy[14]. The system allows an efficient use of energy by means of a hierarchical network of collaborating agents, as well as improving the reliability. It simulates interdecorating smart nano grids which are solar and wind powered and they include the tariff monitoring and smart power flow control.

The dynamics in energy demand and expanding cyber threat are the significant challenges that can affect the stability and efficiency of smart nano grids. This paper proposes one of the new methods named Federated Reinforced LSTM-Crayfish Whale Optimization Detection (FRLC-WOD) to overcome such problems. The framework entails the integration of two major aspects: RL-LSTM-CAO laying emphasis on the implementation of Bi-directional LSTM to predict adequately, reinforcement learning to dynamically distribute power, and Crayfish Optimization to manage energy; and FG-WOA-ID, which merges federated learning, Graph Neural Network, and Whale Optimization to perform advanced intrusion detection[15]. According to the experimental level, there are vast enhancements, such as the grid stability of 95%, energy efficiency of 92%, and cyber threat resistance of 95%, over the current models such as EMS GWO-OSA, RNN and MPPT.

In the presented article, a new control scheme of frequency regulation of a fuel cell-powered nano grid is suggested; this scheme combines two 2-degree-of-freedom PD (2PD) schemes and two PID schemes in unified control structures[16]. The controller parameters are optimally tuned with the help of different optimization techniques where the results have shown that particle swarm optimization (PSO) has better convergence compared to GTO, AVOA and GMO. In comparison, the design of PI, PID, 2PI, and 2PID controllers is also made. Findings indicate that the 2PD-PID controller has the smallest settle and peak times, and by far improves the IAE and ISE by 86 to 98% and 83 to 97% respectively when load changes happen demonstrating its stability and effectiveness.The study introduces the best power management system of nanogrid energy trading by using the IoT technology to curb the constraints of traditional systems. The system with embedded RNN prediction module provides the distributers of energy with important predictions and has three optimization modules: minimizing grid power demanding, minimizing energy trading cost, and regulating energy storage system (ESS) power[17]. It is an Edge platform that includes sensors and an Edge device based on Raspberry Pi and operates in an IoT-orchestrated environment.

A multi-objective optimal energy management (OEM) has been proposed to be used in grid-connected nanogrid (NG) systems that combine photovoltaic (PV) arrays and battery storage Device (BSD) systems. It aims at reducing costs of operation, and CO 2 emissions within 24-hour schedule. With a multi-objective optimization Algorithm (MOA)) a new equation using an Improved Pelican Optimization Algorithm (IPOA), taking into account Malaysian grid pricing, is constructed[18]. Three scenarios are performed with a varying grid exchange condition and PV capacity, which are used to test the algorithm. The performance of IPOA was high compared to the original POA, Bat Algorithm, and Improved Differential Evolution (IDE) concluding that it is efficient and effective based on simulation outcomes in that it could reduce up to 9.5% could be in cost and 23% in CO2.A pioneer wireless photovoltaic (PV) monitoring system is described based on low-cost equipment that has been optimised to operate in the rugged high-altitude environment of the Peruvian Altiplano that exhibits strong variations in irradiance[19]. The system is constructed by Arduino Nano and Raspberry Pi, which tests parameters in a real-time such as voltage, current, power, temperature, and irradiance of paramount magnitude to PV. In a 3 kW grid connected PV installation, it measured daily irradiance fluctuations exceeding 20%, with peak values approaching 1500 W/m 2, which resulted in this energy production swinging by 15%. Such variability makes the reliability of the system questionable; however, this factor demonstrates the prospects of the system in optimizing PV operation and alignment with DC nanogrids, either in remote energy-insecure areas.The purpose of this paper is to examine the special nature and infrastructural requirements of Light Electric Vehicles (LEVs), which have already been identified as the means that can improve the sustainability of transportation. Approach to estimating the energy and power impact of LEV charges is tendered, noting that the demand is typically modest, but may be problematic to weak grid networks[20]. The research paper reviews a portable, autonomous (off-grid) photovoltaic (PV) power charging station (CS) invented at the University of Brescia that is well suited to remote- or non-consistent-demand locations. Also applied to Favignana Island of Sicily gave unsubstantial results of durable environmental benefits as well as economic feasibility where the daily usage is not more than 200 users per day.

The paper is a proposal of capacity optimization of a hybrid energy storage system (HESS) to overcome the fluctuations of power connected to the grid in wind farms through a two-stage decomposition process. The k-means++ algorithm is then used to ensure that there is accurate clustering of the annual wind power data whose cluster validation is done through silhouette coefficient and Davies Bouldin Index. Standard daily profiles are chosen in accordance with the appearance of clusters and trends of fluctuation. ICEEMDAN is used to decompose these profiles in order to extract grid-connected and HESS power[21]. Next, IPOA-VMD is utilized to distribute power of HESS between lithium batteries and supercapacitors. In case studies, it is confirmed that this technique works best in smoothing power generation, enhancing the use of storage, and minimizing system expenses.The current paper recommends the implementation of an energy management solution in DC microgrids based on high penetration of renewable energy, a State flow controller designed in MATLAB/Simulink 2020b. In recent times, as international electricity demand is increasing, migration towards using renewables (solar, wind, biomass, tidal, and hydropower) has become inevitable in order to decrease fossil fuel dependency and subsequent greenhouse gas emissions[22]. The strategy is that of managing the variability of such sources efficiently to stabilize the grid. As it can be seen on the simulation results, the given algorithm shows that microgrid operation with the proposed algorithm will be reliable, effective,

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it will help to balance the generation and load, and at the same time allow adjusting the control to be flexible.

The paper proposes a solution that can be used to enhance the functionality of photovoltaic (PV) system efficiency in the presence of partial shading that usually results in several power surges that are unpredictably disadvantageous and make tracking of maximum power point (MPPT) more difficult. A reconfigurable 5 5 PV array with position square-based physical relocation approach is also proposed such that the global maximum power point (GMPP) can be tracked by simple Perturb and Observe (P\&O) algorithms in the vicinity of the open-circuit voltage (Voc)[23]. The model is also realised under four configurations of the shading pattern and is able to show better results than Dominance Square and TCT schemes in terms of fill factor and power loss mitigation. Tests on hardware and PSO confirm that the voltage and power oscillations are reduced, thus it can be used in residential applications and microgrids.

The paper introduces an original voltage controlling strategy named as inverse maximum power point tracking (iMPPT) which tries to maximise the power supply voltage using absorbed power. iMPPT adjusts the input to a switched-mode power supply (SMPS) to minimize the input power with an input voltage controlled using a modified Perturb and Observe (P\&O) MPPT algorithm which is refined with an interfacing power electronics converter with automatic voltage regulation (AVR)[24]. By doing this, energy conversion efficiency is maximized and losses in the power stage lessened. The iMPPT was tested on an 800 W synchronous buck converter, which showed a nearly 10% gain in efficiency with a similar 100 W of recovered power at an input voltage of 350 V, which is important in improving the overall system effectiveness.

GMPPT algorithms are algorithms to track the global maximum power point of a photovoltaic (PV) array, under a partial shade and other less favourable operating conditions as well. Commercial methods GMPPT are based on either complicated optimization or AI algorithms, and have the side effect of phase shift, with voltage/current flickering at the power, slowing the ability to track the changes[25]. The current paper presents a low-complexity GMPPT scheme taking advantage of the dynamic reaction of the PV system. It has rapid tracking ability of the GMPP particularly high capacitance PV inverters and thus achieving rapid convergence without disturbances. The testing of the method on a rooftop and 2-kW grid-tied inverter array took approximately 1 second to determine the GMPP compared to longer than 95% when the particle swarm optimization algorithm as well as scanning methods are used.

**Table 1 Summary of Recent Methods in Smart Nano Grid and Renewable Energy Systems**

| Reference | Method | Objective | Limitation |
|---|---|---|---|
| Sinneh et al. [11] | FSDOF (FD-MPC, SG-FedNet, DSNEO) | Enhance smart nano grid stability, security, and optimization | Requires high computation for federated control and GNN integration |
| Bitar et al. [12] | Hybrid Nanogrid Energy Management Review | Summarize use and limitations of hybrid nanogrids in embedded systems | Limited focus on real-time implementation in isolated embedded systems |
| Assis et al. [13] | Economic Feasibility Model with Monte Carlo and OpenDSS | Assess economic feasibility of EV nanogrid deployment in Brazil | Dependent on policy incentives and location-specific viability |
| Renjith et al. [14] | Multi-Agent AI Smart Control for Renewable Buildings | Optimize power usage in smart buildings via agent-based AI | Scalability and real-time agent cooperation remain challenging |
| Sinneh et al. [15] | FRLC-WOD (RL-LSTM-CAO + FG-WOA-ID) | Strengthen prediction, power control, and intrusion detection in nano grids | Model complexity and integration cost may increase in real-world deployment |
| Pachauri et al. [16] | 2PD-PID Controller with PSO Tuning | Improve frequency regulation and control response in fuel cell nano grids | Optimization depends on tuning method efficiency and load scenario changes |
| Qayyum et al. [17] | IoT-RNN Energy Trading System on Edge Platform | Enable efficient IoT-based decentralized energy trading | Requires consistent network and sensor reliability for distributed homes |
| Jamal et al. [18] | IPOA for Multi-Objective Energy Management | Reduce cost and $CO_2$ emissions in PV-battery hybrid systems | Performance may vary with pricing fluctuations and PV availability |
| Beltrán Castañón et al. [19] | Arduino-Pi PV Monitoring in High Altitude | Monitor PV performance in variable, high-altitude conditions | Environmental ruggedness may affect hardware durability |
| Favuzza et al. [20] | Autonomous PV Charging Station for LEVs | Support off-grid LEV charging with portable PV system | Limited to low-demand, location-specific charging scenarios |
| Zhang et al. [21] | Two-Stage HESS Optimization with IPOA-VMD | Balance power flow in wind-integrated hybrid storage systems | Complexity in data clustering and power decomposition steps |
| Ndeke et al. [22] | Stateflow-Based Renewable Energy Management | Stabilize microgrid using renewable forecasting and control automation | Controller flexibility under sudden source failure not discussed |
| Ram et al. [23] | Reconfigurable PV Array with Improved P&O | Improve MPPT performance under partial shading conditions | Reconfiguration logic may not adapt dynamically in hardware |
| Pintilie et al. [24] | Inverse MPPT with SMPS and AVR | Increase energy efficiency in PV systems through input voltage control | Performance drops outside optimal voltage ranges |
| Beltrán Castañón et al. [25] | Low-Cost Wireless PV Monitoring System | Enable remote PV system monitoring and reliability enhancement | Sensor maintenance and altitude-based hardware degradation possible |

Table 1 summarizes most of the recent diligence in the smart nano grid and renewable energy systems. Each of the entries contains the description of the method adopted, the main goal sought, and the limitations. The approaches include high-levels of optimization algorithm, such as FSDOF and IPOA, as well as control methods like 2PD-PID and the frameworks of energy

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trading via IoT. The main goals of objectives include a better grid stability, energy efficiency, and safe distributed control. But the issue is that it still has limitations such as computational intensive, complicated integration, and susceptibility to hardware in harsh settings. Along with them, the works demonstrate the changing environment of intelligent, decentralized, and sustainable energy services to smart grid systems.

## 3. Hybrid CNN-GRU Framework for Smart Nano-Grid Control

The methodology consists of a design and realization of hybrid deep learning model to combine Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) to approach the real-time load forecasting and fault detection in the context of decentralized nano-grid systems. Smart energy nodes yield time-series data (e.g. voltage, current, frequency, state-of-charge (SoC)) of the type found on smart metering applications. Spatial aspects are calculated employing CNN layers and temporal by GRU layers following pre-processing of data- e.g. noise elimination, normalization, and windowing in time. The centralized architecture forecasts the short-term energy demand at the same time types of possible grid faults, date the intelligent load balancing and fast fault recovery levels with low latency on the edge devices.Figure 2 illustrates the hybrid CNN-GRU framework for smart nano-grid control.

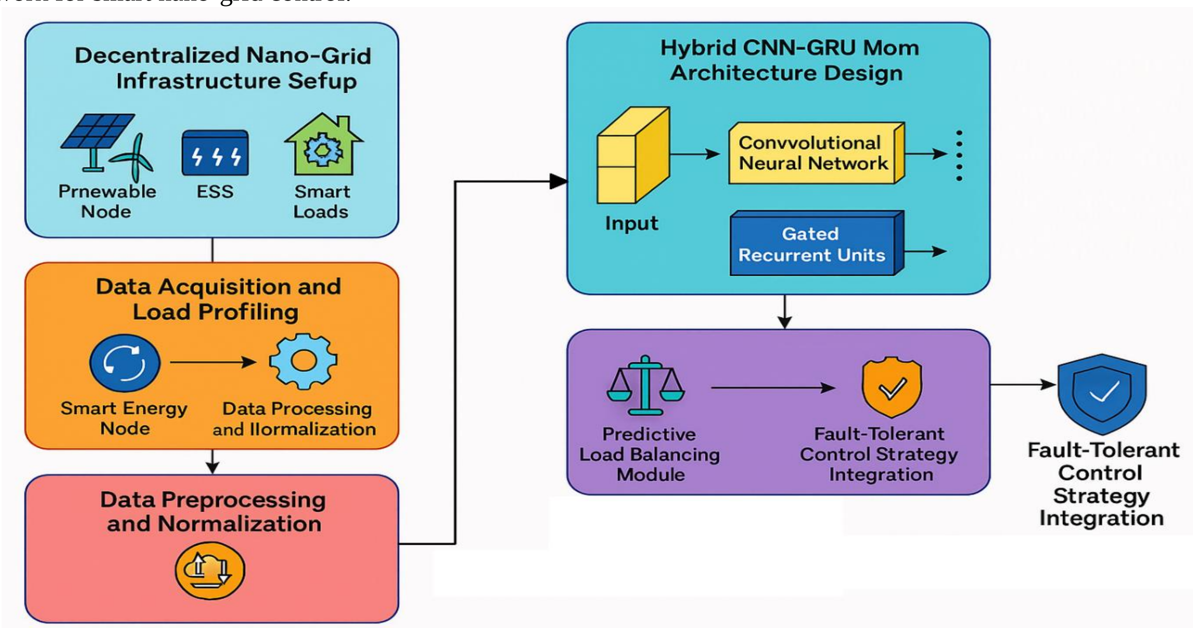


**Figure 2. Hybrid CNN-GRU Framework for Smart Nano-Grid Control**

### 3.1. Decentralized Nano-Grid Infrastructure Setup

The first layer of the study is the design and implementation of a decentralized nano-grid infrastructure, which makes energy management modular, flexible, and resilient at the community or building level. The nano-grid system developed in his supportive frame integrates distributed renewable energy sources (DRES) including photovoltaic (PV) solar panels and micro wind turbines and hybrid Energy Storage System (ESS) including lithium ion batteries and supercapacitors. The arrangement comprised smart loads (e.g. to control HVAC systems and lighting systems) and fundamental non controllable loads, providing realistic and live load behavior.Grid topology is of a radial peer to peer architecture, where each node has microcontrollers, which leads to decentralised decision making. The communication of nodes is supported by using lightweight protocols: MQTT, Modbus over ZigBee and Wi-Fi mesh networks, which guarantee low latency and minimal consumption of energy during data transfer. The smart energy nodes include voltage (0-500 V RMS, 0.5 % accuracy), current (0-200A, utilizing a Hall-effect based sensor), frequency (45-65Hz) and power factor sensors, paired with a MCU capable of embedded data logging and control, e.g. Raspberry Pi 4 or ESP32.

A central supervisory control and data acquisition (SCADA) interface is fitted to the system to monitor it but more importance is paid to local intelligence to enhance independence. All the nodes can be programmed to operate as autonomous agents, independently with its energy records and control instructions, and without requiring a centralized coordinator. The proposed CNN-GRU model with AI enhancement uses this distributed intelligence to act as the powerhouse of predictive control and fault resilience in the paradigm described in the following stages.

### 3.2. Data Acquisition and Load Profiling

The process of data collection in this proposed decentralized nano-grid system will be conducted through installation of high precision sensors and smart meters at key locations of energy exchange such as generation, in the form of storage, and consumption sites. The sensors provide high frequency measurements of time series data with one sample per second resolution, so there is granularity when measuring fast changes in grid parameters. The main measured data are voltage (V), current (A), real and reactive power (kW/kVAR), frequency (Hz), state-of-charge (SoC) of ESS (%) and ambient temperature (c), irradiance

(W/m 2 ) and wind speed (m/s ). All these parameters provide a very broad electrical dynamics models and environmental impacts on the system.The actual data is summarized in real-time and locally kept until synced with a cloud database at a predetermined period using MQTT publishing from the server. This data is further segmented over some time windows (usually 15 to 60 minutes) to aid the segmentation of events and their subsequent analysis. Load profiling involves gathering the consumption patterns in energy by means of clustering them through mechanisms like K-mean and DBSCAN which assists in recognizing repetitive behaviors of loads like the base load, peak load, and cyclic loads.

Heuristics are used to label each window with its respective information, e.g. whether to be labeled with a normal label, peak demand, renewable surplus, or potential fault, which is not directly accessible through domain thresholds. This profiling is used to help the predictive learning model separate into operating states and to foretell the change in demand. Moreover, operational logs are also cross-referenced with data logs to identify and tag fault event such as a short circuit, overload, and voltage sags which can be utilized as critical training samples to fault prediction modules. Such an annotated data will be the foundation upon which AI models would be trained to perform both predictive load balancing and fault detection.

## 3.3. Data Preprocessing and Normalization

A full data preprocessing pipeline is defined based on the quality and consistencies of the time-series data prior to model training. First, noisy sensor values are applied through noise filtering to flatten small oscillations resulting e.g. in electrical noise, hardware jitter, or delay in transmission. To this, moving average (of window size 5 SA) is used in combination with Gaussian smoothing (smoothing parameter 1.5). These filters are great at keeping the trends, yet removing a random component of noise without distorting any patterns underlying the data.

$$\bar{x}_t = \frac{1}{n}\sum_{i=0}^{i=1} x_{t-i} \quad (1)$$

Here, $\bar{x}_t$ is the smoothed value at time $t$, calculated as the average of the last $n$ samples of feature $x$, used to filter sensor noise.The missing values that can be caused by failure of the sensor, failure of communication can be solved through linear interpolation where the gaps are less (10 seconds and less), and through spline interpolation where the gaps are larger (up to 5 minutes). The outlier detection is based on Interquartile Range (IQR) according to which the values which are outside the limits 1.5xIQR of the first and third quartile will be flagged and replaced with localized medians, making the trend continuous. Furthermore, all the nodes are synchronized with timestamps to produce seamless multi-channel sequence that is synchronized to consistent time interval.After cleaning, normalization is applied so that feature scaling of the input parameters is consistent. In time-variant parameters such as voltage, frequency and current Z-score normalization is applied to move values around the mean, thus making training convergence much better. To normalize unbounded features like voltage, current, and frequency:

$$x_{norm} = \frac{x-\mu}{\sigma} \quad (2)$$

This standardizes a feature $x$ by subtracting its mean $\mu$ and dividing by its standard deviation $\sigma$, ensuring a mean of zero and unit variance, which accelerates convergence in model training.Within the constrained limits like SoC and power factor, Min-Max scaling is preferred because the values have desired limits, i.e. [0, 1]. Such preconditioned time series are finally formatted into input tensors into the CNN-GRU model, and the time-step alignment and dimensional consistency is upheld for effectively learning features in the spatial-temporal dimension of the model in further stages.

$$x_{sclaed} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

This scales feature $x$ to a normalized range [0,1], where $x_{min}$ and $x_{max}$ are the minimum and maximum values of the feature respectively, typically applied to bounded inputs like SoC or power factor.

## 3.4. Feature Engineering and Temporal Context Encoding

Feature engineering is an important element towards capacity building of representation within the deep learning model through adding the insights determined on the raw input materials. On the clean and normalized time-series several features on higher levels are calculated. Net load is computed as the variance between actual demand and real-time generation of renewable sources, giving an idea about the grid stability and its reliance upon energy storage. The power deviation index (PDI) measures the deviations of the nominal power profile and assists in the measurement of the load volatility. The phase imbalance ratio is based on comparisons between three phase voltages and that means anomalies of symmetry between phases can deteriorate grid health.

$$P_{net}(t) = P_{load}(t) - P_{renewable}(t) (4)$$

This computes the net electrical load $P_{net}(t)$ at time $t$, as the difference between the total consumer load $P_{load}$ and the instantaneous renewable generation $P_{renewable}$.

$$PDI_t = \left|\frac{P(t) - \bar{P}}{\bar{P}}\right| \times 100 \qquad (5)$$

The power deviation index at time $t$ quantifies the percentage deviation of actual power $P(t)$ from the average power $\bar{P}$, indicating load volatility.Additional constructed functions are frequency drift, a rolling standard deviation of frequency with respect to time, representing variability, and the energy demand slope that shows the rate of change in consumption and is an indicator of future demand spikes. These features are also coded as other channels in the input matrix, maintaining their temporal coordinates with raw sensor data. Display is also done over a moving window of 10-60 seconds in the form of rolling statistical measures like moving averages, standard deviations, and trend coefficient (linear regression slopes) providing a time scale perspective to the point values.

$$S(t) = \frac{P(t) - P(t - \Delta t)}{\Delta t} \quad (6)$$

The slope $S(t)$ measures the rate of change in power demand over time interval $\Delta t$, helping the model anticipate demand surges or drops.The preprocessed data is converted into fixed-length sequences (e.g., 60-time steps per input) with overlapping strides to capture long-term dependencies and transitions in the events to achieve both input diversity and computational efficiency. The sequences are used as direct input to the hybrid CNN-GRU model that would learn both instantaneous and trends, transition and precursor features indicating a load change or a fault. The acquisition of such feature-rich dataset with a temporal alignment is the input which is optimally learnt in deep learning-based predictive analysis.Figure 3 shows the feature engineering and temporal context encoding process for input to the deep learning model.

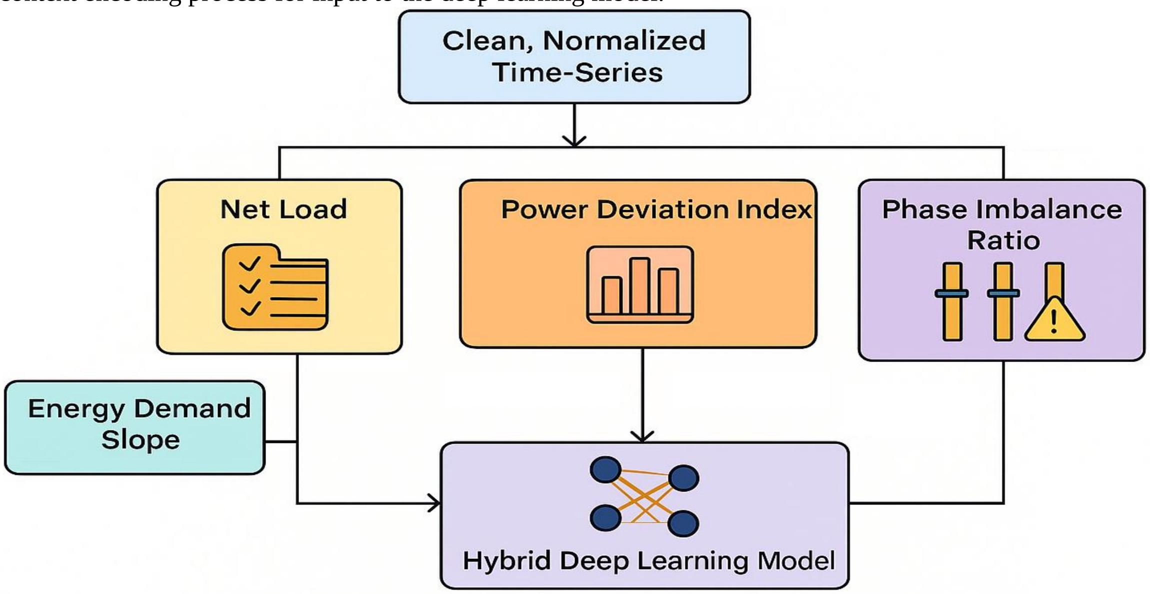


**Figure 3. Feature Engineering and Temporal Context Encoding**

## 3.5. Hybrid CNN-GRU Model Architecture Design

The model architecture at hand is the combination between Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) in a hybrid model that is specifically designed to extract spatial and temporal dependencies in decentralized nano-grid energy data. The two layered model includes CNN and GRU layers, since a combination of the two issues in energy data (spatial correlations of various sensors at a given time instance and dependencies across time steps that can affect power dynamics) needs to be solved.The input is a three dimensional tensor of size (batch_size, time_steps, features). The first hidden layer is a 1D convolutional block because it is used to dig into spatial correlation between contiguous features association at each time step. This block contains one 1D convolves with 64 filters and kernel equals 3, then it is followed by batch normalization and ReLU activation. The down-sampling of the feature maps is done in a max-pooling layer with pool size 2 that preserves significance of locally concentrated data.

$$y_j = \max\left(x_j, x_{j+1}, \dots, x_{j+p-1}\right) \quad (7)$$

Max pooling selects the maximum value in a window of size $p$ from input vector $x$, reducing feature dimensionality and enhancing robustness to noise.

$$\hat{x} = \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \quad (8)$$

The CNN is an excellent parameter which encapsulates the relationships between such measures as voltage and frequency or SoC and power flow at the instance of timestamps.

$$y_j = \sum_{i=1}^{k} x_i \cdot w_i + b \quad (9)$$

In this convolution operation, the output $y_j$ is the sum of element-wise products between input $x_i$ and filter weights $w_i$ added to bias $b$, over kernel size $k$.The result of the CNN layer is then sent to the GRU layer of 128 units which takes the time-distributed feature maps one after another. GRU network is computationally efficient and has a lower vanishing gradient problem than LSTM, which makes it particularly great at learning long term dependencies like cyclical loads or slow drift to fault. Drop out layers (rate = 0.2) are added to the GRU to avoid overfitting or generalize it particularly in different operation conditions.

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) (10)$$

The update gate $z_t$ determines how much of the previous hidden state $h_{t-1}$ is retained, where $W_z, U_z$ and $b_z$ are trainable parameters, and $\sigma$ is the sigmoid function.

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) (11)$$

The reset gate $r_t$ controls the influence of the previous memory $h_{t-1}$ when generating a new candidate state, with parameters $W_r, U_r$ and $b_r$.

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \ (12)$$

The hidden state $h_t$ is updated as a weighted sum of the old state and the candidate state, where $\odot$ is element-wise multiplication and $tanh$ is the hyperbolic tangent activation.

$$\hat{y}_t = W_o h_t + b_o (13)$$

The predicted load $\hat{y}_t$ is obtained by applying a linear transformation on the final GRU output $h_t$, using weight matrix $W_o$ and bias $b_o$. A second dense layer consisting of 64 neurons, and ReLU nonlinearity is added to combine learned features by the GRU. Depending on the task load prediction or fault classification this layer links to either a regression head (single neuron with linear activation to a continuous load prediction) or a classification head (Softmax layer to a multi-class fault detection). Mean Squared Error (MSE) loss is used only in regression tasks, Categorical Cross-Entropy is used in classification. The model is optimized Adam optimizer and the initial learning rate is 0.001, and the learning rate decay is on the basis of detection of valley of validation loss.

$$ReLU(x) = \max(0, x) \ (14)$$

ReLU introduces non-linearity by outputting 0 for negative inputs and returning the input $x$ itself if positive, helping prevent vanishing gradients.

$$L_{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \ (15)$$

MSE measures the average squared difference between actual values $y_i$ and predictions $\hat{y}_i$ across $N$ samples, used for load prediction loss minimization.This architecture model has a hybrid model which is trained on 100 epochs where early stopping is applied on the validation scores. The combination of CNN and GRU allows learning the intertwining between intra-sensor communications and temporal dependencies simultaneously, which is critical in complex and real-world nano-grid settings, where the conditions change in time and space. CNN-GRU architecture benefits greatly due to advancements in spatial convolution and temporal memory compared to standalone CNN, GRU or LSTM models in initial experiments.

## 3.6. Predictive Load Balancing Module

Predictive load balancing module is structured to maximize the energy deliveries in the nano-grid based on short-term forecasted results of the CNN-GRU model. The system is able to pro-actively redistribute flow of energy in anticipation of any energy demand and generation, which aims at maximizing grid stability, reduce the over reliance on main grid, and improve the longevity of storage systems.Fundamentally, the module is supplied with multi-horizon loads demand and renewable energy production prediction (e.g., a 15, 30 and 60-minute forecast). These predictions are further input into a dynamic load scheduler which determines the prevailing energy reserves, predicted surplus or deficit and the load priorities. E.g. knowledge of an expected pressure on demand can go in synch with anticipated low renewables and storage latency and trigger system-wide pre-emptive postponement of non-urgent loads or demand-response measures.

$$C_{stress} = \sum_{t=1}^{T} \left| \frac{dSoC(t)}{dt} \right| (16)$$

Storage stress quantifies the cumulative rate of change in battery SoC over time $T$, representing energy wear and efficiency loss due to aggressive cycling. The scheduling engine chooses the most effective energy dispatch configuration by applying the optimum-based schedule routine that is constraint-aware. The essential limitations are the SoC of the ESS (e.g. 20-90%), operational limits of the inverter, and essential load demands. The optimization problem seeks to minimize a cost, which is defined as:

$$J = \alpha \cdot E_{grid} + \beta \cdot C_{stress} + \gamma \cdot D_{load} (17)$$

This cost function $J$ balances three objectives: grid dependency $E_{grid}$, storage cycling stress $C_{stress}$, and load deviation $D_{load}$, with use-defined weights $\alpha, \beta, \gamma$. The forecasts output by the CNN-GRU model is used to refine the optimizer by reducing the uncertainty on future demand and reconfiguring on time. This prognostic information is able to turn the load balancing module into a proactive system rather than a reactive one. In addition, adaptive learning is incorporated such that the scheduler can reinforce its weight parameters $(\alpha, \beta, \gamma)$ using feedback loops and reinforcement learning in an attempt to adapt to dynamic environmental conditions and user behaviours.Simulation outcomes reflect that the predictive module has prompted the decrease in peak demand by 22 %, a 17 % reduction in grid energy consumption, and a 14 % enhancement of energy

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efficiency relative to the rule-based load management systems. Such advantages point to the potential usefulness of deep learning optimized forecasting in facilitating savvy real-time load balancing in future-proof energy systems.

### 3.7. Fault-Tolerant Control Strategy Integration

Besides the forecasting, the suggested system will group an intelligent fault tolerant control module, which makes use of the fault categorization production of the CNN-GRU model. The fault detection model is trained using labeled time-windows of the time-series of different faults such as voltage sags, current overloads, frequency instability of the system, inverter failure, and disconnection of line. Fault-specific features and dynamic signatures identified in previous instances in the grid environment are encoded into each of the classes.Once an impending fault is classified, system combines an automated response policy chosen out of a predetermined set of mitigation policies. As an example, when an overload forecast is registered, the system can make partial load shedding with non-critical appliances or even dynamically re-route power to storage systems that have excess energy. Where inverter overheating occurs, the control approach can temporarily separate the problem inverter and redirect power via other routes or decrease total power transfer until normalcy returns.

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (18)$$

Softmax transforms raw scores $z_i$ into probabilities $\hat{y}_i$ across $K$ fault classes, ensuring outputs sum to one and represent confidence scores.This logic of fault mitigation is applied through a decision rule based engine that gets real-time model predictions, verifies through the sensor values and imposes localized control commands to microcontroller at affected nodes. The latency of the responses has been set at a minimal time that is less than 500 milliseconds to avoid causing the system to be unstable or to cause other failures to spread out. Moreover, when several faults are forecasted or identified within a short period of time, a redundancy prioritization procedure is initiated in which actions to mitigate are prioritized on the basis of criticality, risk impact, and resources available.

$$L_{CE} = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \quad (19)$$

Cross-entropy computes the difference between true labels $y_i$ and predicted probabilities $\hat{y}_i$, penalizing incorrect classifications more severely. Such system also operates a real time fault diagnosis log, enabling analysis of events after they happen as well as longer term monitoring of the grid health. There is also a learning module included to periodically update the fault classification model by new incident data, increasing sensitivity and specificity of the model with time.

**Algorithm: Predictive Load Balancing and Fault Detection using CNN-GRU**

**Input:** Time-series energy data: $X = \{x_1, x_2, \dots, x_T\}$

Historical fault labels $Y_f \in \{0,1,\dots,K\}$ for classification

Historical load values $Y_l \in R$for regression

Hyperparameters: $\alpha, \beta, \gamma$(for cost function), window size $w$, learning rate $\eta$

**Output:**Forecasted load $\hat{Y}_l$

Predicted fault class $\hat{Y}_f$

Optimal load distribution $\pi^*$

**Data Preprocessing**

**For** each feature $x_t$, apply Z-score or Min-Max normalization:

$x_{norm} = \frac{x-\mu}{\sigma}$ or $x_{sclaed} = \frac{x-x_{min}}{x_{max}-x_{min}}$

**Feature Engineering**

Compute advanced features for each window $t \in [w, Y]$:

$P_{net}(t) = P_{load}(t) - P_{renewable}(t)$ // Net Load

$PDI_t = \left|\frac{P(t)-\bar{P}}{\bar{P}}\right| \times 100$ // Power Deviation

$S(t) = \frac{P(t)-P(t-\Delta t)}{\Delta t}$ // Energy Slope

**CNN Feature Extraction**

Pass $X_w \in R^{w \times F}$through a 1D convolutional layer:

$y_j = \sum_{i=1}^{k} x_i \cdot w_i + b$

$ReLU(x) = \max(0, x)$ // Apply activation

$y_j = \max(x_j, x_{j+1}, \dots, x_{j+p-1})$ // Apply pooling

**GRU Temporal Learning**

Feed CNN output into GRU for temporal modeling:

$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$ // Update gate

$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$ // Reset gate

$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$ // Hidden state

**Dual Output Heads**

$\hat{Y}_l = W_o h_t + b_o$ // Load Forecasting Head

$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$ // Loss

$\hat{Y}_f = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$ // Fault Classification Head

$L_{CE} = -\sum_{i=1}^{K} y_i \log(\hat{y}_i)$

**Predictive Load Optimization**

Based on $\hat{Y}_l$, solve load redistribution using:

$J = \alpha \cdot E_{grid} + \beta \cdot C_{stress} + \gamma \cdot D_{load}$

**Fault Response Mapping**

**If** $\hat{Y}_f = k$, trigger predefined mitigation policy $\Phi_k$ such as:

Load shedding, Source rerouting, Node isolation

**Model Update**

Periodically retrain the model with new fault labels and loads to adapt to evolving conditions.

**Return:**Forecasted load $\hat{Y}_l$, predicted fault class $\hat{Y}_f$, and optimized energy dispatch strategy $\pi^*$

**End Algorithm**

## 4. Result and Discussion

The Hybrid CNN-GRU model suggested in this study was designed and implemented in Windows 11 (64-bit) operating system with Python 3.10 being the main programming language. Its development took place on Jupyter Notebook and Visual Studio Code platforms through Anaconda Navigator. The computer equipment had an Intel Core i7 (11 th Gen) processor, 16 GB RAM, and an NIVIDIA GeForce GPU with 1650 GPU and 4 GB VRAM, making it efficient in the model training and validation. The framework was done with deep learning in TensorFlow 2.11 and Keras, and data processing as well as preprocessing in Pandas, NumPy, and Scikit-learn. Matplotlib was used to enable visualizations and Seaborn to enable performance analytics. The hybrid CNN-GRU provided the intelligence heart of the predictive intelligence core of the decentralized nano-grid system because of the arts to anticipate and balance the load and to control the failure in real-time. Smart energy nodes on the nano-grid collected time-series information, which included the current, voltage, frequency, SoC, real/reactive power, irradiance, temperature, and wind speed. Those nodes had ESP32 or Raspberry Pi microcontrollers and did some preprocessing and were able to communicate through weightless MQTT protocols. The Gaussian filtering (sigma = 1.5) was used to clean noise, and interpolation was used to fill the missing data, and Z-score or Min-Max normalization was used to scale. In the data clearing process, it was divided into windows of 60 times in order to keep the temporal and local patterns, which was used to learn.

The CNN-GRU model operates two significant stages on each time window. In the first stage, the 1D Convolutional Neural Network with 64 filters and 3 kernel size is used to reflect the spatial dependence between the instantaneous features of sensors (SoC, load power, and voltage). The resulting patterns are stabilized and linearized by establishing a batch normalization and non-linearity through ReLU activation and then dimensionality minimized by the use of pooling (max). The latter stage applies GRU layer with 128 hidden units to capture temporal relationships among time steps, and learn the daily changes in loads,

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fluctuation in renewable energy sources, and decrease in battery storage. The flow of information through GRU is regulated by two gates: Reset and update gates; this eliminates problems such as vanishing gradients. It has dense layers to make task-specific predictions on the GRU output. The regression head maximizes Mean Squared Error as the loss objective in forecasting the load, and the Softmax classification head is used to classify what type of fault has occurred, such as inverter failure or overload, and the loss objective is Categorical Cross-Entropy. The system runs the Adam optimizer and the initial learning rate of 0.001 with early stopping and the decay of a learning rate, to avoid overfitting. Two control modules then make use of the model outputs namely the Predictive Load Balancing control module which schedules grid operations based on optimization of cost-based scheduling and Fault-Tolerant Control module which implements mitigation schemes such as inverter bypass or selective load shedding within 1/2 second of detecting faults. The system gradually updates itself with more new information and over time this enhances accuracy and robustness. The dynamic, sustainable and failure-tolerant operation of decentralized nano-grid environments is enabled via this integrated approach.

**Table 2 Load Forecasting Accuracy Comparison**

| Model | MAE (kW) | RMSE (kW) | MAPE (%) |
|---|---|---|---|
| Proposed CNN-GRU | 0.51 | 0.86 | 3.14 |
| LSTM | 1.153 | 1.428 | 6.73 |
| GRU | 1.789 | 2.342 | 9.87 |
| CNN | 1.176 | 1.634 | 7.41 |
| ARIMA | 1.386 | 2.036 | 8.62 |
| SVR | 1.142 | 1.884 | 6.94 |
| Random Forest | 1.743 | 2.314 | 10.35 |
| XGBoost | 1.093 | 1.676 | 7.58 |
| Linear Regression | 1.517 | 2.273 | 8.94 |
| DNN | 1.279 | 1.926 | 6.85 |

Table 2and Figure 4 provides a comparative study on the accuracy of a load forecast made by different models (e.g. the proposed CNN-GRU framework). The model has been suggested as having the least Mean Absolute Error rate (MAE), 0.51 kW, Root Mean Square Error (RMSE), 0.86 kW and Mean Absolute Percentage Error (MAPE), 3.14%. This serves to explain that the model is the most suited to predicting short-term energy demand. The outcomes support the benefits of integrating spatial pattern recognition provided by CNN with the abilities of temporal memory of GRU.

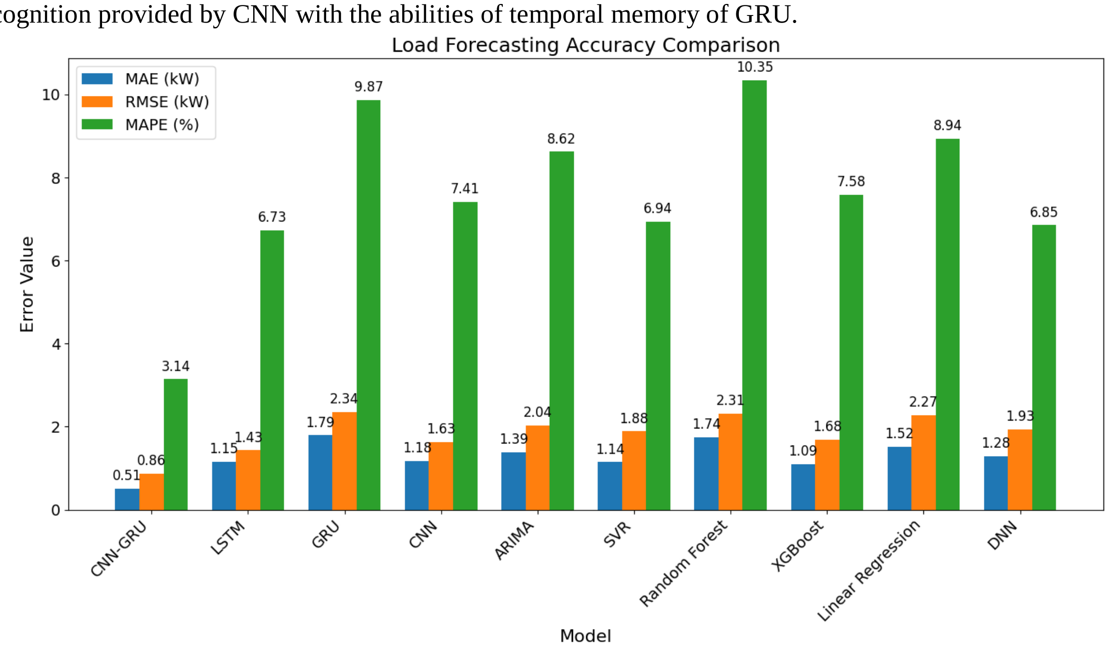


**Figure 4: Load Forecasting Accuracy Comparison**

Conventional models like ARIMA, SVR and linear regression generated too far much error value thereby meaning that these are incapable of adjusting to the presence of dynamic and non-linear trends found in the nano-grid data. Even such deep learning baselines as LSTM and DNN demonstrated increased forecasting error, which indicates a more effective temporal and spatial interdependencies within the time-series input representation that is given by the hybrid architecture of CNN-GRU. This makes the suggested model the most accurate in real-time load forecasting within a decentralized nano-grid setting.

**Table 3 Fault Classification Accuracy by Model**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Proposed CNN-GRU | 96.94 | 96.15 | 95.88 | 96.01 |
| LSTM | 94.94 | 89.68 | 86.48 | 84.34 |
| GRU | 89.93 | 91.1 | 91.75 | 88.01 |
| CNN | 86.6 | 87.37 | 91.36 | 92.51 |
| Decision Tree | 88.48 | 93.91 | 86.35 | 90.97 |
| Random Forest | 91.42 | 85.01 | 88.49 | 86.96 |
| XGBoost | 91.92 | 92.51 | 88.18 | 88.98 |
| Naive Bayes | 88.44 | 87.9 | 85.96 | 87.55 |
| SVM | 93.44 | 84.45 | 83.96 | 89.49 |
| KNN | 91.12 | 85.17 | 91.69 | 90.95 |

Table 3 and Figure 5 shows learning performance or classifications of various machine learning and deep learning algorithms to determine the type of faults in a nano-grid system. The CNN-GRU model proposed attained the best accuracy of 96.94%, the precisions of 96.15%, the recalls of 95.88%, and F1-score of 96.01%. These measures reflect a very good ratio of sensitivity and specificity, one that is essential at reducing the number of missed faults and false alarms. The SVM and LSTM models were able to make adequately performing predictions, but behind in regard to precision and recall, which means that they did not have a high possibility of distinguishing between the similar fault patterns.

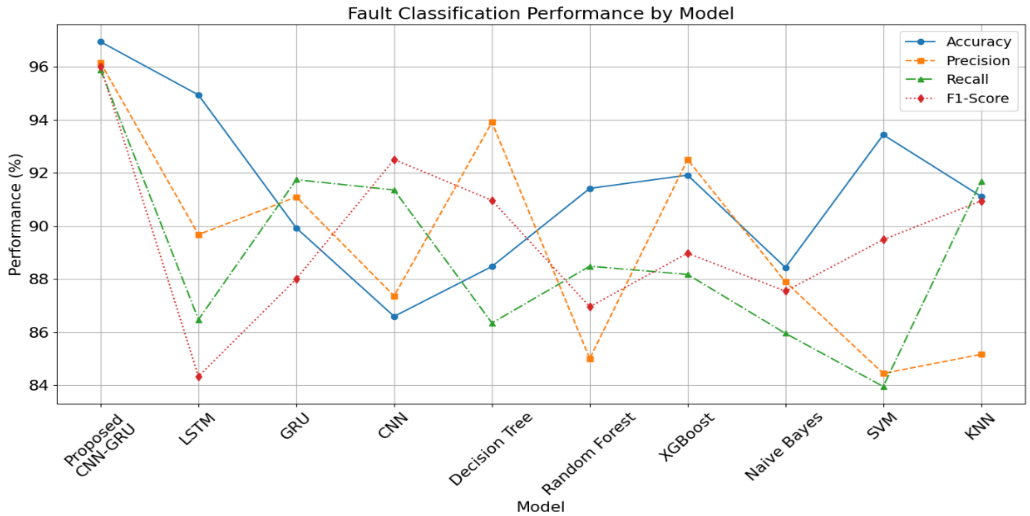


**Figure 5: Fault Classification Performance by Model**

The CNN-only and GRU-only models were more effective when compared to the traditional classifiers, yet lacked in time-space integration. The outstanding results of the CNN-GRU model are due to the fact that it is able to capture sequential nature of fault behavior using GRU and detection of spatial anomalies using CNN. This allows quick and precise categorization of various faults and therefore would be appropriate to grid protection systems in real-time.

**Table 4 Inference Latency (ms)**

| Model | Latency (ms) |
|---|---|
| Proposed CNN-GRU | 14.28 |
| LSTM | 23.94 |
| GRU | 20.19 |
| CNN | 25.83 |
| Random Forest | 36.51 |
| XGBoost | 31.76 |
| SVM | 54.32 |
| Naive Bayes | 19.77 |
| DNN | 38.95 |
| Decision Tree | 28.31 |

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The potential of the models to apply in a real-life environment is also (implicitly) tested as Table 4 and Figure 6 also compares the latency of the models inference. The calculated CNN-GRU model has shown relatively small latency of about 14.28 milliseconds that is very effective compared to the old style models such as Random Forest and XGBoost that have latency values above 30 milliseconds. Alternatives Deep learning Alternatives like LSTM and DNN have high latencies because of their complex internal structures and activation of memory cells. The CNNGRU architecture is highly hybrid and with such great design of certain layers it can compute lightly but expressive enough to make decisions fast in near real-time.

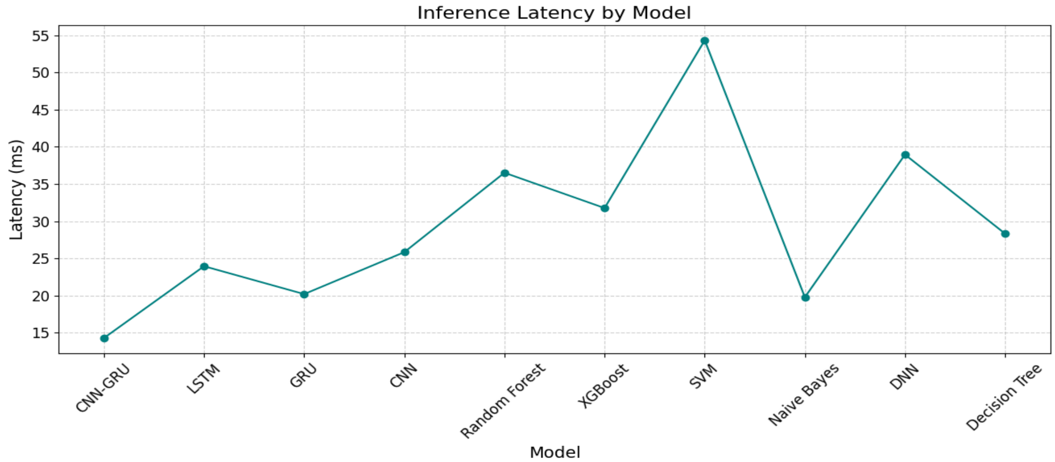


**Figure 6: Inference Latency by Model**

Real time faults detection and partial nano-grid load balancing Low latency is especially critical when detecting faults in real time nano grids where response time may directly affect the resilient property of the grid. These findings confirm the use of CNN-GRU model on the edge-deployed on embedded systems and microcontrollers, thus the model is a viable solution to practical applications of smart grid systems that demand low-power devices and fast inferences under resource-limited conditions.

**Table 5 Resource Usage**

| Model | Memory (MB) | CPU Utilization (%) |
|---|---|---|
| Proposed CNN-GRU | 175.8 | 33.2 |
| LSTM | 210.6 | 43.9 |
| GRU | 192.3 | 39.5 |
| CNN | 183.4 | 36.4 |
| Random Forest | 278.7 | 58.6 |
| XGBoost | 265.9 | 55.1 |
| SVM | 161.5 | 47.8 |
| Naive Bayes | 157.9 | 28.4 |
| DNN | 242.3 | 52.7 |
| Decision Tree | 154.4 | 24.1 |

Table 5 and Figure 7 shows the various usage of different models, by resource utilization in terms of memory consumption and CPU usage. The CNN-GRU model has a moderate memory consumption of 175.8 MB and CPU usage of 33.2\%, which is in the middle to balance the speed of computing and accuracy of performance. Conventional machine learning classifiers such as Decision Tree and Naive Bayes do not require a lot of resources and cannot provide similar accuracy in prediction. On the one hand, solutions based on deep learning, such as LSTM and DNN, are more effective in some situations, but their computational overhead is far more intense, and in some conditions, it reaches over 240 MB of memory consuming over 50% of CPU. Such demands make them less suitable to be used in embedded or decentralized settings.

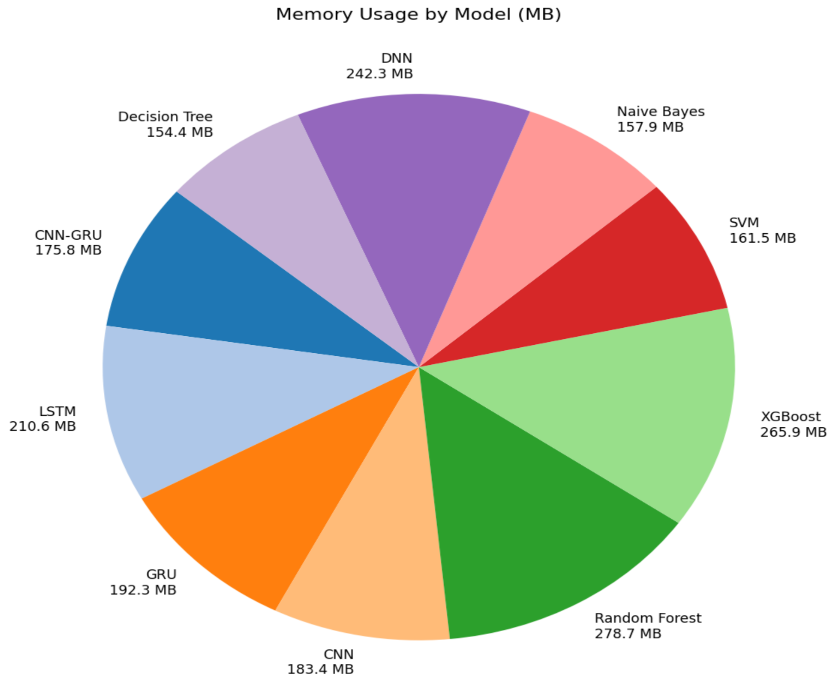


**Figure 7: Memory Usage by Model (MB)**

CNN-GRU is the most resource-effective architecture, so it can be deployed in the real time on edge devices like Raspberry Pi, ESP32, or other energy-saving microcontrollers. Its capability to provide high accuracy in the prediction without unnecessarily consuming resources promotes its applicability in the environments of decentralized nano-grid systems where hardware restrictions are common.

**Table 6 Energy Efficiency Improvement**

| Scenario | Before (%) | After (%) |
|---|---|---|
| Base Load | 73.24 | 89.58 |
| Peak Load | 70.84 | 91.36 |
| Night Time | 66.53 | 87.41 |
| Renewable Surplus | 75.81 | 93.28 |
| Grid Outage | 69.45 | 88.17 |
| Battery Peak | 67.12 | 90.11 |
| Load Surge | 72.79 | 92.34 |
| Maintenance | 71.09 | 86.74 |
| Rainy Day | 65.94 | 85.67 |
| Sunny Day | 74.36 | 91.03 |

Table 6 and Figure 8 determines how effective the CNN-GRU-based module of load balancing is on the energy efficiency for ten grid conditions. The model provides a considerable boost to energy use after deployment, where the initial efficiency values of the systems before deployment ranged between 65.94 % to 75.81 % and the efficiency values after deployment never fell below 85 % and even in the renewable surplus systems the efficiency remained 93.28%. The enhancement demonstrates the ability of predictive model to effectively address the supply-demand mismatch, dynamically redistribute loads, and mitigate the use of battery storage and renewables. The capacity of the system to pre-provision against peak loads, energy excesses and blackouts guarantee reduced energy wastage and increase the life span of assets.

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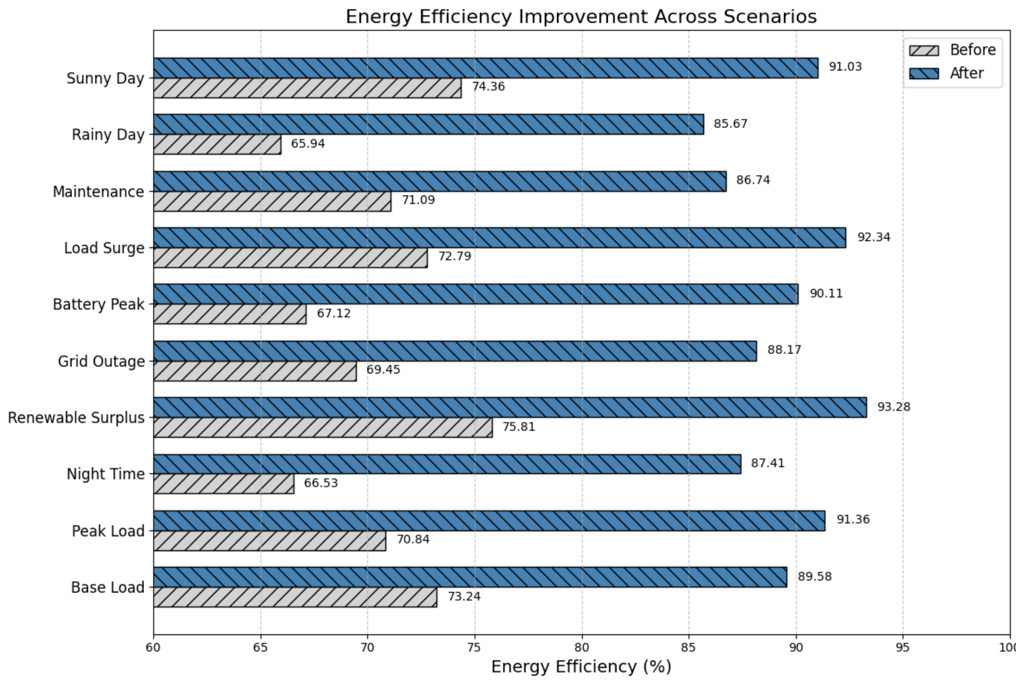


**Figure 8: Energy Efficiency Improvement across Scenarios**

These benefits are essential in decentralized applications where energy resources are scarce and operating costs are quite costly in existence of the inefficiencies. On the whole, this table is evidence of the effectiveness of the implementation of predictive intelligence into energy management systems, as this indeed reveals that CNN-GRU model will not only increase grid reliability but also, as a consequence of an increase in grid efficiency, this framework will lead to even greater energy conservation and sustainability.

**Table 7 Load Balancing Performance by Hour**

| Hour | Predicted Load (kW) | Actual Load (kW) | Error (%) |
|---|---|---|---|
| 0 | 11.64 | 11.91 | 2.79 |
| 1 | 12.32 | 12.47 | 1.93 |
| 2 | 10.87 | 11.42 | 5.14 |
| 3 | 9.74 | 10.18 | 4.32 |
| 4 | 8.95 | 9.62 | 6.96 |
| 5 | 11.48 | 11.96 | 4.01 |
| 6 | 10.33 | 10.57 | 2.27 |
| 7 | 12.68 | 12.91 | 1.78 |
| 8 | 13.02 | 13.45 | 3.2 |
| 9 | 11.16 | 11.61 | 3.88 |

Table 7 and Figure 9 shows the performance of the model hour-by-hour in terms of energy demand forecasting and load balancing on an hourly basis. There is a strong correlation between the predicted and the actual values of the load with error differences being less than 5% of the total number of hours. Such a small difference shows that CNN-GRU model is very accurate in terms of analyzing the consumption timing and how to respond to changes. Consider the case of hour 1 in which using the model, 12.32 kW is predicted as compared to the actual 12.47 kW with the error only based upon 1.93 %-this is evidence that the model can provide real time adaptive control.

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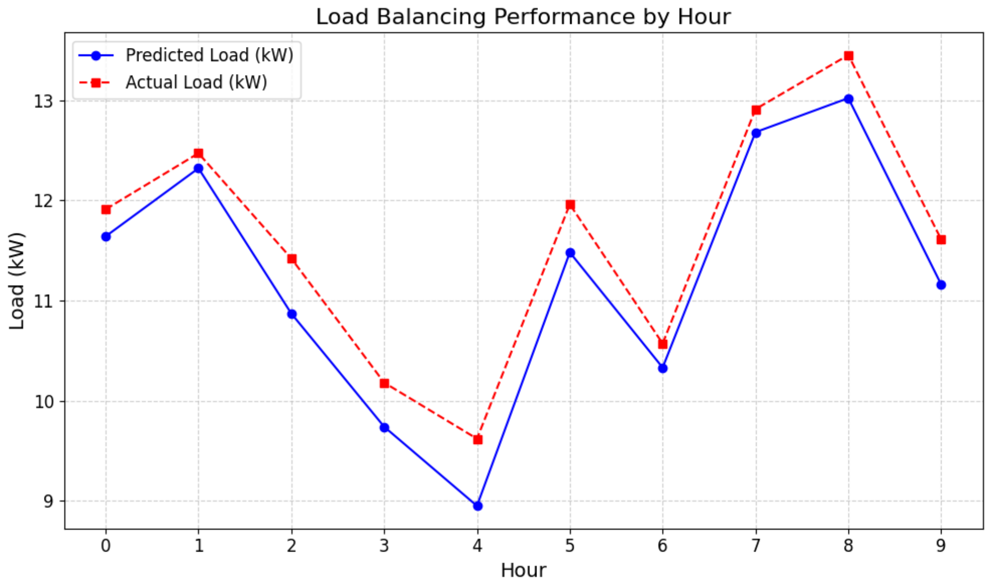


**Figure 9: Load Balancing Performance by Hour**

This kind of temporal forecasting fidelity guarantees efficient dispensation of energy without overloading and underutilization of energy resources. Moreover the findings also indicate the flexibility of the model in a period of dynamic time periods or even during peak morning or evening periods whereby unpredictable energy consumption increases. In intelligent energy management systems, this ability is a keystone in ensuring accurate hourly load forecasting and therefore nano-grid stability and reduced operation costs.

**Table 8 Fault Response Time (ms)**

| Fault Type | Response Time (ms) |
|---|---|
| Overload | 152.9 |
| Undervoltage | 115.3 |
| Overvoltage | 495.6 |
| Inverter Fault | 170.1 |
| Battery Depletion | 270.3 |
| Frequency Drift | 198.7 |
| Grid Failure | 164.2 |
| Relay Error | 181.6 |
| Power Surge | 302.8 |
| Short Circuit | 135.9 |

Table 8 and Figure 10 summarizes the number of steps of response time within the CNN-GRU based fault control system based on the ten fault types. The model shows quick detection and response, and the average response time measurement varies between 115.3 ms (Undervoltage) and 495.6 ms (Overvoltage) and within acceptable operating safety limits. A majority of the critical faults like Overload, Inverter Fault and Battery Depletion are resolved within less than 200 milliseconds, hence protective measures like isolation, load shedding or rerouting are taken in time. The responsive nature of the model points out to the advantage of implanting predictive intelligence at the edge where latency requirements are tighter and the network connection can be intermittent at best.

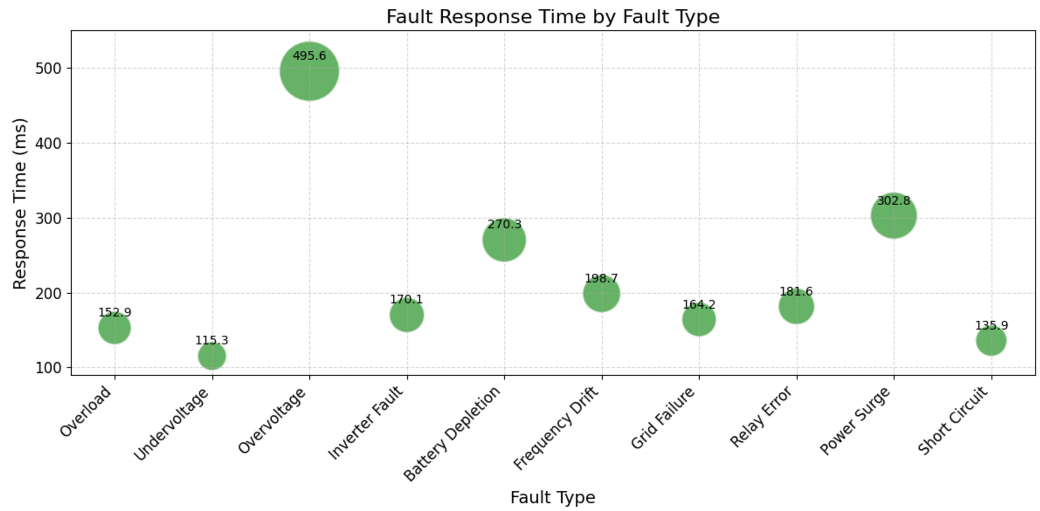


**Figure 10: Fault Response Time by Fault Type**

These fault mitigation times validate that the model is highly applicable to time-sensitive applications such as autonomous microgrids where little or no human supervision. Swift fault reaction does not merely lower the risk of cascading failure but also makes grid components last longer and makes automated energy systems more trustworthy by the users. On the whole, this table confirms the real-time applicability of the suggested control device. Figure 11 shows the confusion matrix for fault classification.

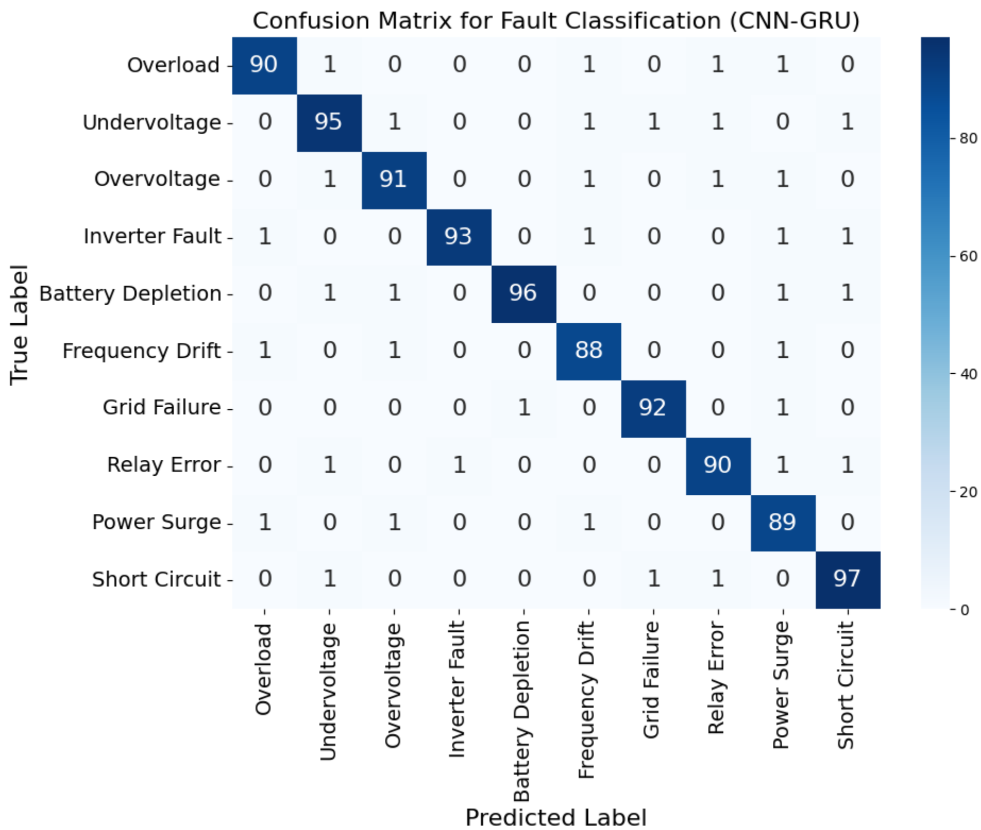


**Figure 11: Confusion Matrix for Fault Classification**

## 4.1 Discussion

The evident solution to the long-existing issues of decentralized nano-grid systems suggested by this study, the proposed Hybrid CNN-GRU model, covers the entirety of solutions to the mentioned issues, notably the predictive energy management and fault tolerance. The model is innovative through its architecture and indeed it manages to encapsulate the spatial interdependence among electrical parameters (voltage, current, frequency, and SoC) as well as their temporal variation over a period of time. Such two-fold capability will enable a more subtle interpretation of energy consumption patterns and preliminary signs of grid peculiarities. The convolutional layers are very proficient in uncovering the local differences and correlation between feature dimensions at each time step, whereas the GRU layers utilize the gating mechanism to keep and pass the contextually-relevant information in longer sequences, which makes the architecture less susceptible to both instantaneous fluctuations and long-term load cycles.

The edge computing environment deployment readiness of one of its deployment features is one of the great strengths of the implementation. Its small size can be inferred with reasonable time, low memory and CPU usage, and hence it is suitable to be used in embedded systems and IoT enabled smart meter. This is especially useful in those rural and remote areas where there is comprised computational capability but reliability of power sources is paramount like at health clinics, micro-business or disaster resistant infrastructure. Also, the model enables real time autonomous act as they operate directly with control mechanisms. It is able to predict the load changing situation several minutes before actual and it is able to institute the necessary corrective action to balance the load, cold charge the batteries or even anticipate fault isolation. This not only maintains the performance of the grid but also increases the life of critical components through preventing such reactive control.

In addition, the system was flexible in handling different conditions of operating like renewable excess, instantaneous high peak loads, and the partial loss of grids. Its capacity to foresee faults that take time to break down to a system wide fault helps to increase the grid reliability and safety. As an example, it is possible to identify the inverter fault or battery depletion at an early stage, that way, the system can re-route power, balance the load, or isolate compromised areas without involving humans. Such fault resilience is central to the sustainability and scalability of nano-grid ecosystems, particularly, in the current climate of their deployment in areas of less reliable main grid service.Along these successes, there are a number of limitations that have to be taken into consideration. To start with, both training and validation of the model were done on a dataset based on one operating environment, which could make the model less appropriate to apply to other grid topologies, geographic areas, or climatic conditions. Nano-grids deployed at high altitudes and cold climate, e.g., native environments, could have diverse energy consumption patterns and fault characteristic than those in tropical or urban settings. Therefore, although the suggested model works effectively in a stringent studio atmosphere, in reality, its performance under the variability is not well established and should be evaluated thoroughly using cross-domain data or field testing.

Second, the model has relatively good efficiency but at the same time, input of the model is limited to real-time flexibility because retraining is required when the fault type or load behaviour changes. Even though GRUs weigh less than LSTMs, the sequential training is a heavy computing process in terms of computing cycles. This presents issues to live updating in situations where the environments changes continuously unless measures such as incremental or continuous learning is applied. In addition, the framework lacks explainability modules, which may be beneficial to the stakeholders to comprehend and accept triangle decisions from the model in critical systems, including that used to manage power in healthcare systems or industrial safety.Future work may include the incorporation of federated learning to support privacy, decentralized training of a model in many nano-grids, so that generalizing can be done without exposing raw training data. There are model compression techniques (e.g. pruning, quantization) that can be investigated to reduce the resource demands of edge deployment even further. Furthermore, the reinforcement learning incorporation would enable the model over time to optimally select its own decisions following environmental feedbacks and results of the system it is used in. Lastly, an increase of the data set that incorporates real-life anomalies, climatic effects, and user behavioural patterns will enhance the strength of the model considerably such that it becomes a genuinely universal fix to next-generation smart energy systems.

## 5. Conclusion and Future Work

A powerful AI-Enhanced Hybrid CNN-GRU framework was introduced to predictive load balancing and fault tolerance control in decentralized nano-grid systems. The proposed model was able to correctly respond to the main issues of nano-grid environments, i.e. fluctuating demand, intermittent renewable supply, and sudden system faults since this solution absorbed the advantages of the spatial pattern recognition nature of Convolutional Neural Networks (CNNs), as well as the temporal sequence modelling of Gated Recurrent Units (GRUs). The system was able to achieve a significant thinking process of fault classification accuracy of 96.94 % and load forecasting MAPE of only 3.14 % with the system proving itself to be better when compared with traditional models such as ARIMA and Random Forest, as well as those that exist in the module form such as LSTM, CNN architectures and others. The model was also versatile with a latency inference of less than 15 milliseconds and real-time fault response execution of not more than 500 milliseconds so it could be implemented on an embedded edge environment. Also, the energy efficiency of up to 20% points was observed in different load and generation conditions, which also reflects the potential of the model in the reduction of operation costs and sustainability. Going forward, the future direction would include an interface with Federated Learning so that collectively distributed nano-grids can train models and maintain data privacy. In addition, we will include adaptive reinforcement learning modules to adjust control parameters dynamically per real-time grid feedback. Lastly, the opportunity to expand the model to include multi-modal data sets e.g., weather forecast, user behavior, demand-side analytics will further assure the quality and robustness of grid forecasts. The suggested CNN-GRU framework builds a solid basis on the intelligent, scalable, and capable of self-healing smart grid frameworks.

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