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Power Quality Assessment in Grid-Connected Solar PV Systems Using Deep Learning Techniques

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Abstract

To address challenges in stability, power quality, and computational demands while supporting sustainable energy goals in grid-connected solar PV systems, this research introduces a novel deep learning approach: Adaptive Graph-Aware Reinforced Autoencoder with Attention-Based Neural Architecture Search (AGRAAN). AGRAAN simplifies and accelerates the development of neural networks by automatically identifying optimal architectures through Neural Architecture Search (NAS), enabling efficient learning from limited data using Few-Shot Learning, and enhancing performance through attention mechanisms for time-series forecasting. This integrated approach reduces manual tuning and adapts effectively to various tasks. High levels of solar PV integration in power grids introduce variability due to weather conditions and limited forecasting, often resulting in high operational costs. To address this, the AGRAAN model enhances real-time solar variability prediction, improving adaptability, cost-efficiency, and grid stability. NAS supports architectural optimization, Few-Shot Learning improves adaptability with minimal data, and attention mechanisms enhance forecasting accuracy. Additionally, high PV penetration causes voltage fluctuations and harmonic distortions in diverse grid environments. To mitigate these effects, a complementary system named Graph-Aware Reinforced Autoencoder Control System (GRAACS) is proposed. GRAACS detects and manages power quality issues using Autoencoders for anomaly detection, Graph Convolutional Networks (GCNs) for spatial prediction, and Reinforcement Learning for adaptive real-time control. The combined AGRAAN and GRAACS models significantly enhance performance, achieving a high efficiency score of 0.98, an F1-Score of 0.97, and a low Mean Absolute Error (MAE) of 0.11. These results demonstrate the effectiveness of the proposed AI-driven framework in optimizing solar PV grid integration for energy efficiency.

Keywords: Stability, Power Quality, Variability, Forecasting, Adaptability, Efficiency, Grid Stability, Voltage Fluctuations, Harmonic Distortions, Energy Efficiency

1. Introduction

Electrical power production dependent on photo-initiated physical processes, which get to be progressively implanted in the electrical framework before long nowadays driven via sustainable methods at huge intensity i.e., solar photovoltaic (PV) systems. Solar power generation is the process of converting sunlight into electricity using PV cells or solar thermal systems. This clean and renewable energy source plays a crucial role in reducing reliance on fossil fuels and minimizing environmental impact. These technologies help to ensure the seamless and accurate operation of grid connected PV systems which as everyone know suffer unique challenges due to solar being a variable, intermittent energy resource. The current power electronics technology, along with the advent of deep learning approaches could be instrumental in addressing some challenges and greatly improving performance, robustness as well as efficiency.

Before this generated energy is injected into the grid, managing it by power electronics plays a significant role on PV systems. This entails changing the direct current (DC) that solar panels output into alternating current (AC) at a frequency and voltage suitable for feeding directly back in to the grid. While power electronic devices such as inverters and converters used in a system for a power conversion [1], [2]. Power Conversion processes have become more

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efficient nowadays, due to the latest developments in Power Semiconductor technologies like Wide Band-Gap devices. The new power electronics technologies are suitable to for operation at higher voltages, frequencies and temperatures as resulting the reduction of overall energy losses during conversion and increase in life-time of power electronic components [3]. Modern power semiconductors have seen significant advancements, primarily in Silicon (Si), Silicon Carbide (SiC), and Gallium Nitride (GaN) technologies. Traditional Si-based devices, like IGBTs and MOSFETs, are cost-effective and widely used but have limitations in efficiency and high-frequency operation. SiC semiconductors offer higher efficiency, faster switching speeds, and better thermal performance, making them ideal for high-power applications like renewable energy systems. Also advanced control algorithms have been integrated to the controllers which allows a more accurate and faster power flow control, this increases grid stability by improvement in both system reliability/reduced faults at consumer end (power quality) as well [4].

Over the past half decade, deep learning has emerged as a solution to these difficult problems in FPV system grid integration. Deep learning models are more powerful to predict the solar power generation [5], [6], optimize the operation of renewable energy resources and even that can make effective fault detection and diagnosis process with available large datasets, complex architectures which were infeasible otherwise using traditional methodologies. For example, deep learning models including convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to predict PV power output over short time durations with a high degree of accuracy based on different factors within their environment [7]. However, with the growing field of deep learning in power electronics for grid-connected PV systems will not permit without face some challenges. The answer has a lot to do with the fact that deep learning models need large quantities of data (and it strictly prefers good quality version) in order for them us to train. Unlike traditional power grids, its difficult to obtain the data in the context of solar PV grids due to the systems are highly variable, Limited historical data available, Data Collection Challenges, Variability in Environmental Conditions and Heterogeneity of PV Systems. Moreover, the computational complexity of these models can be an obstacle to applying them in real time for power electronic systems [8]. Nonetheless designs of simplified models and further research on making them as interpretable/reliable in dynamical worlds [9], [10].

Grid-connected PV systems can be looked upon as what the future holds for us i.e. a combination of high-end power electronics being integrated with deep learning algorithms to seamlessly reside on the already in place system without any stretch or hassle and simply doing wonders upstream! This integration will allow more optimal energy management, better failure detection and an improved grid stability [11]. In addition, with the development of more powerful learning models for deep infrastructures arising from emergent paradigms that require exploration and future research when it comes to optimization methods on entire power electronic devices operation in real-time will lead to energy systems having better efficiency [12].

Lastly, integration of advanced power electronics and deep learning constitutes one of the most exciting areas for future room in grid-tie PV systems. Although still in development, the idea of using dry and molten salts for heat storage has great potential to be highly effective from both an efficiency and reliability standpoint though it may not always represent a low energy source. The use of these technologies in global grid-scale power generation, as the demand for renewable energy continues to rise and new melting systems are explored [13], [14], [15]. The main contribution of this content is follows:

The issue of managing fluctuating generation output in real-time grid incident risk evaluation is addressed by the novel Adaptive Attention-Based NAS with Few-Shot Learning by optimizing neural networks for accurate short-term forecasting, reducing manual tuning and infrastructure costs, enhancing, and reducing accuracy, and improving prediction and extreme value accuracy, and, in turn, grid stability.

The elevated solar photovoltaics (PV) penetration leads to issues voltage fluctuations and harmonic distortions is resolved by the innovative Graph-Aware Reinforced Autoencoder Control System (GRAACS), using autoencoders for real-time anomaly detection, using GCNs for impact prediction, and utilizing reinforcement learning (RL) for dynamic grid control, promoting grid stability and reliability.

This paper is organized in the following manner: Section 2 deals with the literature review, Section 3 details the proposed technique, Section 4 presents the results and the discussion, and Section 5 concludes the study.

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2. Literature Review

Diaba et al. [16] developed a deep long short-term memory (LSTM) method for the accurate predictive power of PV, which used historical NIST and for short term forecasting. This work applies the methodology for short-term PV power generation forecasting using IoT data, and compares the output of the proposed algorithm with a deep RNN model, to corroborate the methodology. In the comparison study, the present approach seems to offer high degree of accuracy and short-term PV power output prediction as compared to the deep RNN model. Thus, the report offers important policy implications for stakeholders and decision-makers in the energy sub-sectors. Verification of the proposed technique was conducted using data of the real-world PV electricity generation. But it was, of course, unnatural to have more brightness or sunlight in a country that belonged to the Nordic region especially in winter.

Cheng et al. [17] proposed an ANN with ML base for RES including solar power arrays, distributed field wind farm, and lithium-ion battery clusters. For the purpose of generating training data for multivariate RES machine learning models, it formulated a Monte Carlo simulation approach that uses conventional nonlinear EMT models. The proposed heterogeneous CPU-GPU ECS architecture was data-oriented and applies for several system sizes and gets rather good GPU performance and highest computational accuracy. It has, but unlike other aspects involved in computational optimization such as model complexity which has been enhanced. This was said, however, only on average and regarding to the fact that the proposed models was slightly slower than other MLPs of the same system scale in terms of the execution time, which they were about two- to three-fold. This caused a decrease in the rate of acceleration to the number of tactical practicalities necessary per day.

Nallakaruppan et al. [18] offered a rich Explainable Artificial Intelligence (XAI) approach for elaborating on the AI black box models so as to foster the predictability and distribution of solar energy's utilization and control. These effects of key parameters such as, solar irradiance, module temperature, ambient temperature was analyzed using a model-agnostic approach called the Local Interpretable Model-Agnostic Explainable (LIME). Apart from explainability, the application of XAI techniques in solar power generation fixes challenges that emanate from the parameters in the solar radiation pattern analysis, the solar performance error estimation, and function degradation of the battery. Further, it provides easy to understand information that helps extend the durability of solar panels making the development of sustainable energy technologies better. However, due to this, solar electricity posed many challenges and complicated the methods of interconnection with other electrical systems. These were such as variation in the production of solar energy.

Abdullah et al. [19] provided a framework that described as data led and that supplied information to predict the weather for the hybrid renewable energy system through its lifetime as well as forecast the optimal size of the system. The approach combines machine learning and the hybrid metaheuristic type. Applying light gradient boosting machine, cat boost regressor and extreme gradient boosting as the specific machine learning tree ensemble techniques, the framework was used to forecast the hourly solar radiation and the load demand. The intended approach was to develop a closer, more realistic hybrid renewable energy system capacity that was more reliance and environmentally friendly and at the same time was in a position to meet all the system necessities. The guidelines provide an effective way of sizing and assessing hybrid renewable power systems within the context of weather changeability all through the life cycle of the system. In order to discern whether the new proposed data-driven approach of making HRES sizing estimates was more accurate other than the Yearly-based simulations more research was needed.

Dev et al. [20] provided an effective way of managing frequency in Microgrids (MGs) employing a Sliding Mode Control (SMC) based on Teaching Learning (TL) optimization. The objective of this study was to enhance the frequency stability of the MGs and this was crucial mainly when incorporating intermittent renewable energy sources. In making the system robust against nonlinearities and parameter variations, the parameters of the SMC were tuned with the aid of the TL algorithm. To check one or the other aspect of the design that was under different operating conditions MATLAB simulations were performed. It was worth mentioning that some of these simulations include typical nonlinearities, fluctuation of system parameters and has incorporated the random step load disruption as seen in real life [21]. However, chattering a term used to describe high-frequency oscillations in the control action was a major disadvantage for the SMC approach. It was mostly associated with the choice of the wrong controller gains.

Lee et al. [22] imposed an approach for pre-processing data that can estimate the missing values of meteorological and power generation data using K Nearest Neighbor (K-NN) with linear Regression. Employing historical data an AI model was employed to identify outliers and those parameters with high correlation with power generating volumes that were substantially higher. This work has also validated the above data pre-processing technique by developing multilayer perceptron (MLP) and long short-term memory (LSTM) models whereby specific power generation was forecasted for the seventeen solar photovoltaic plants in the short- and medium-terms. But how much of these pre-processing and modelling methods' computational costs and resource utilization were not addressed in the papers, thus making these methods practically impossible to implement in a situation where resources are scarce.

From the above study it is clear that, in [16] impacts PV power prediction accuracy, in [17] the proposed model is slower than other MLPs, limiting real-time application, in [18] solar energy variability complicates interconnection with other electrical systems, in [19] requires further research to validate the new data-driven HRES sizing approach, in [20] chattering in SMC is a major drawback due to inappropriate controller gains, in [21] random PQD events and noise complicate real-time system classification, in [22] computational costs of pre-processing and modeling methods are not addressed, in [23] difficulty in accurately identifying wind turbine parameters under uncertainties, in [24] limited applicability to more complex and large-scale system identification problems, in [25] minimal principle solution complexity increases with system parameter changes. Hence a novel is need to address these challenges.

3. Proposed Methodology

The integration of solar PV systems into modern power systems is vital in a world transitioning to sustainable energy alternatives. Solar PV is known for its ability to produce clean and sustainable energy which also generates a reduction in greenhouse gas emissions. This is critical to ensuring energy security in a reliable and affordable way. This research employed deep learning techniques to enhance the optimization of solar PV systems to increase efficiency, reliability and otherwise address real-time integration issues critical to making solar PV more viable for grid integration that in the end support this sustainable energy goals. The goal of this research is to enhance the system efficiency and reliability, address the challenge of incorporating complex, computationally intensive models that adapts to variable conditions while ensuring stable grid operations. However, integrating solar PV into power grids has presented significant challenges in grid stability, power quality, and system optimization. The deep learning models require significantly high computational requirements, real-time performance, and adaptability. Therefore, a novel "Adaptive Graph-Aware Reinforced Autoencoder with Attention-Based NAS (AGRAAN)" was implemented in this approach. Figure 1 illustrates the AGRAA architecture.

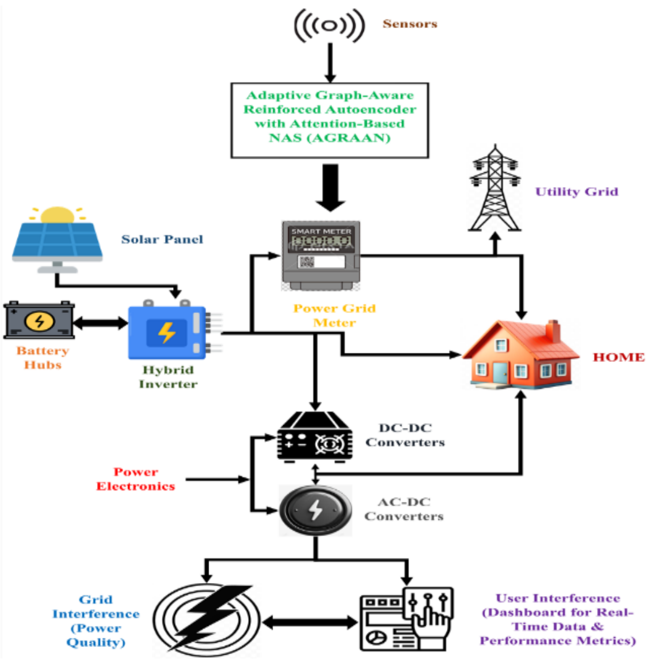

Figure 1. Architecture of Proposed AGRAAN with the Power Grid Connected PV System

Figure 1 illustrates the AGRAA, consists of an advanced grid management framework to perform integration and operational function of a solar PV grid management system. The AGRAAN enhances solar PV grid integration through management of power quality issues, obtaining energy from solar panels and battery hubs into a hybrid inverter that integrates a DC to AC conversion. The component of the PV grid management system consists of DC-DC converters, AC-DC converters, a power grid meter to observe the grid, a grid interference option to monitor the grid. The AGRAAN system will consist of a number of sensors that undertake data collection in real-time through algorithms focused on outlier and anomaly detection, grid modelling and dynamic adjustment through reinforcement learning and neural architecture search. The user interface displays performance metrics and real-time operational state of the system. In the architecture of the proposed AGRAAN with a power grid-connected PV system, several key components work together to ensure efficient energy conversion and management. The solar panel captures sunlight and converts it into DC electricity. This power is then processed by a hybrid converter, which optimizes energy flow between the solar panels, battery storage, and the grid. The power grid meter monitors electricity consumption, production, and grid exchange to ensure efficient energy distribution. Grid interference refers to disruptions or fluctuations in the grid that may impact system stability, requiring real-time adjustments. The converter (often an inverter) transforms DC power from the solar panels or batteries into AC power suitable for grid supply or local consumption. Various sensors track parameters like voltage, current, temperature, and irradiance to optimize performance and protect the system. Lastly, the user interface provides real-time monitoring and control, enabling users to manage energy flow, check system health, and adjust settings for optimal performance.

3.1. Adaptive Attention-Based NAS with Few-Shot Learning

In the existing, power grids that have high levels of solar PV installations, real-time management of solar PV variability is a significant challenge. The variability caused by changing weather conditions leads to rapid variations in the PV electricity output. Current algorithms tend to be limited by real-time forecasting, complexities of implementing advanced solutions and significantly high infrastructure costs. Hence, a novel Adaptive Attention-Based NAS with Few-Shot Learning has been introduced, to address an assembly of significant challenges associated with the incorporation of solar PV systems into power grids.

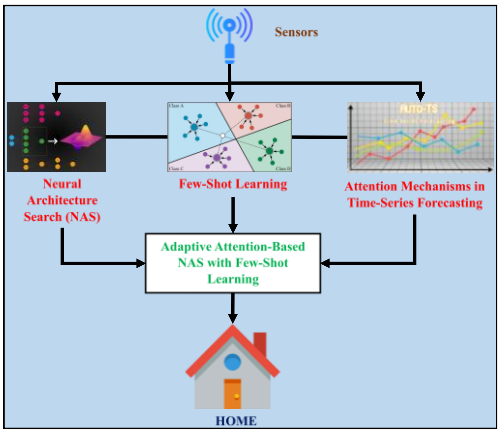

Figure 2. Architecture of the proposed Adaptive Attention-Based NAS with Few-Shot Learning

Figure 2 shows the architecture of the proposed Adaptive Attention-Based NAS with Few-Shot Learning. The main objective of Adaptive Attention-Based NAS with Few-Shot Learning is to a response to the high computational demands and real-time variability issues that are associated with changes in weather and the inherently unpredictable nature of solar PV production. Solar PV production varies rapidly due to fluctuating weather conditions. This approach aims to optimize neural networks in a manner that achieves high forecasting accuracy of solar PV production in real-time. It aims to reduce the computational burden in managing solar PV production in conjunction with power grids through the optimization of deep learning models to forecast solar generation and manage grid resources. It increases the accuracy of forecasting, is able to adapt to infrequent data, decreases infrastructure costs, and improves grid management practices through the optimization of neural networks while minimizing manual tuning. The more details on this technique will be explained in further section.

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3.2. Neural Architecture Search (NAS)

Neural architecture search (NAS) is an automated procedure for designing artificial neural networks (ANNs), a favoured architecture in machine learning. NAS has generated networks, which are equal to, or better than, the best human-designed architecture.

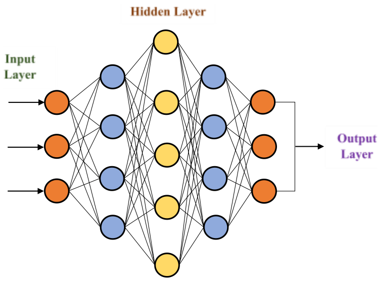


Figure 3. Structure of Neural architecture search (NAS)

Figure 3 illustrates the basic structure of NAS which used for optimization purpose in this approach. One of the critical functions of NAS is it applies algorithms to identify the best-performing neural network architectures for each application. The design process is automated through algorithmically explored variants of layers, connectivity between layers, and architectural parameters, using a systematic exploration of a predetermined space of feasible neural network configurations to discover the best-structured model to optimize performance. NAS is used in this manner as it optimizes deep learning model architectures to forecast variability in solar PV power generation. In systematically identifying the most effective models, NAS thereby improves forecasting accuracy and efficiency of output, thus, improving operational management of solar PV systems through increased forecast accuracy. More accurate forecasts, will improve operational management, and NAS will assist in optimizing the number of computational resources used to modify architecture. NAS will help to increase ease of incorporation of solar PV systems into the grid while enhancing operational management abilities and the value added to the overall power distribution. This will be the NAS objective function for the optimization of deep learning models, primarily for solar PV variability forecasting. Equation (1) is written in this form:

$$\text{Objective} = \text{Accuracy}\ (\mathrm{f_{arch}}) - \lambda \times \text{Complexity}(\mathrm{f_{arch}}) \tag{1}$$

f_{arch} denotes the performance of a neural network architecture, Accuracy measures prediction performance, Complexity measures computational cost. λ is a trade-off parameter balancing accuracy vs complexity. In terms of the Search Space Definition, equation (2) is defined as:

$$\text{Search Space} = \{\text{Layers}, \text{Neurons per Layer}, \text{Activation Functions}, \text{Connectivity Patterns}\} \tag{2}$$

in the Search space comprises several configurations of Layers, Neurons, Activation Functions, and Connectivity Patterns. This Optimization Process is expressed mathematically as shown in equation (3):

$$Optimal\ Architecture = \arg \max_{arch\, \in\, Search\ Space} \left(Accuracy(f_{arch}) - \lambda \times Complexity(f_{arch})\right) \tag{3}$$

This equation searches for the architecture in the space which has maximum value of this objective function, thus balancing accuracy with complexity. Performance evaluation is expressed as shown in equation (4):

$$\text{Performance Metric} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{Loss_i} \tag{4}$$

$Loss_i$ is the loss function value for the i^{th} validation sample, and N is the total number of samples. The obtained metric checks the models against validation data. These formulas are at the core of how NAS is used to optimize neural network structures to improve forecast accuracy at reasonable computational costs.

3.3. Few-Shot Learning

A machine learning methodology known as "Few-Shot Learning" instructs an AI model to produce correct predictions when trained on a small quantity of labelled instances. Typically, this is employed in a classification task for training models with limited data as training examples.

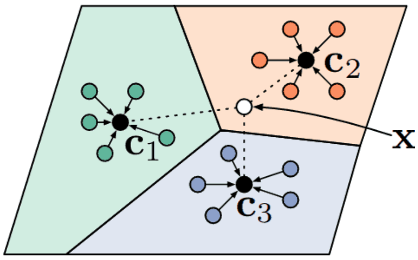


Figure 4. Structure of Few-Shot Learning

The basic structure of Few-Shot Learning is described in the figure 4, which used for adaptability purpose, in this approach. Few-Shot Learning applies sophisticated algorithms to transfer prior knowledge or learning from closely related tasks with little to no data to generalize the learning. The use of methods such as meta-learning or similarity-based approaches allow the architecture to learn with just a few examples and further apply the learning reliably to novel, closely related situations. In this manner Few-Shot Learning enables the approach. Few-Shot Learning is particularly advantageous when data is limited or difficult to obtain such as with rare or extreme weather conditions change solar PV output. Because the traditional deep learning process relies on vast amounts of data to perform accurately, Few-Shot Learning uses the little dataset to train the model. Therefore, the model is able to generalize based on the limited examples, and becomes more effective at predicting and performing management of variability despite scarce historical data. The benefit of efficiently utilizing scarce data, i.e., data is available only in limited amounts, such as the scarcity of historical data for rare weather events (e.g., extreme storms, heavy cloud cover anomalies), which significantly impact the predictability of solar output. These events are not only infrequent but also introduce variability that traditional forecasting models struggle to capture.solar PV's real-time performance making it more flexible and resilient under unpredictable conditions, thereby making it more robust in stabilizing the electricity grid. Mathematically, task-specific model training is expressed for Few-Shot Learning in the domain of solar PV variability prediction, as shown in equation (5):

$$\theta^* = \arg\underbrace{\min}_{\theta}\ E_{T\sim p(T)}[L_T(f_\theta)] \tag{5}$$

θ denotes the model parameters, T is a specific task that is sampled from a distribution of tasks $p(T)$ and a loss function L_T gives the loss for model f with parameter θ on task T. It is to be noted that the goal is to minimize expected loss across all tasks, even when only a few examples are available for each task. Then the Support and Query Sets is shown in equation (6):

$$T = \{(S, Q)\} \tag{6}$$

S refers to the support set containing only a few examples, and is usually labeled. Q is the Query Set containing examples for which the model needs to make a prediction. Using this idea of the model being trained to perform well in Q on the basis of what it has learnt from P, equation (7) describes the Meta-Learning Objective:

$$L_{meta} = \sum_T L_T(f_{\theta^*}) \tag{7}$$

L_{meta} is the meta-learning loss function summing the losses over multiple tasks T. Then, the objective is to learn a model initialization θ^* such that it achieves good performance on new tasks using only a few samples. The adaptation to new data is shown in equation (8):

$$\theta' = \theta^* - \alpha\nabla_\theta L_{T_{new}}(f_\theta) \tag{8}$$

Where, θ' denotes adapted model parameters after a few gradient steps with learning rate α on a new task T_{new}, derived from limited data in extreme or rare conditions.

These equations understand how Few-Shot Learning will make the model generalize and adapt quickly to new, scarce data, making it suitable for the prediction of solar PV output under rare or extreme weather conditions.

3.4. Attention Mechanisms in Time-Series Forecasting

Attention Mechanisms in Time-Series Forecasting is a deep learning technique which calculates the attention weights by making a prediction for every time step in the input. The weights indicate how relevant each time step is to make a forecast. It uses a context vector as the representation of the input sequence attended, which is used while generating with the attention weights. Attention mechanisms dynamically assess and assign importance to individual regions of input data in accordance with how pertinent those different segments are to the task. As a technique used in time-series forecasting specifically, the application of attention mechanisms incorporates a weighted aspect of forecasting, allowing a model to learn to emphasize important time steps or features when forecasting. Attention mechanisms help to improve the forecasting of solar PV output by allowing models to apply varying levels of importance to different periods, features, or patterns when forecasting solar PV power output that is particularly significant to accuracy in forecasting. Traditional models treat all input data in the same "weighted" manner, whereas, with attention mechanisms, each input specifically is afforded differing "weight importance" that is invaluable to the full model learning to focus on important attributes of solar PV variability such as sudden shifts in weather or the consideration of only relevant time intervals, etc. A model that weights a prediction for an important characteristic of solar PV variability will improve overall forecasting accuracy, enabling the energy manager to manage real-time variability in a more reliable and precise manner. This is an important improvement to grid stability and the effective response strategies that support reliable dissemination of solar PV into power systems more generally. The following equation, which shows how attention score is calculated, equation (9), describes the mechanisms that attention is able to enhance the forecasting of solar PV output:

$$e_i = \mathrm{score}(h_i, s) \tag{9}$$

e_i is the attention score for the i^{th} input, h_i is the hidden state (or feature vector) related to that input, and s is the context vector or the previous hidden state. The score function $score(h_i, s)$ tells how much attention should be given to each input. Therefore, the SoftMax Normalization is defined in the equation (10):

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{n} \exp(e_j)} \tag{10}$$

α_i is the attention weight with respect to the i^{th} input, computed through a SoftMax normalisation of the attention scores. This will ensure that all the attention weights add up to 1, hence allowing the model to assign different importance levels to each input. Hence equation (11) defines the Context Vector by Attention-Weighted Sum:

$$c = \sum_{i=1}^{n} \alpha_i h_i \tag{11}$$

c is the context vector, computed as the weighted sum of the input hidden states h_i using the attention weights α_i. The context vector picks up on exactly that information in the input which is relevant for the task at hand like key periods or patterns in solar PV output that impact power generation. In formula, it looks like this: equation (12) Output Prediction:

$$\hat{y} = f(c, s) \tag{12}$$

In this instance, the predicted output refers to forecasted solar PV output, represented as $\hat{y}$. This prediction is dictated by a function known as f which takes into context both the context vector c and state s hence making it possible for model observations targeting specific information to be more precise. These equations explain how attention mechanisms let a model sort out important features or time periods according to their significance in increasing the accuracy and reliability of solar PV output forecasts. It is this kind of focused approach that will enable better handling of real-time variability to eventually improve grid stability and response strategies. The Adaptive Attention-Based NAS with Few-Shot Learning captures this to enable it to incorporate these techniques to mitigate this variability and related computational demands in solar PV integration, making it a very significant development toward the goal of grid performance optimization and thereby support the achievements of sustainable energy goals.

3.5. Graph-Aware Reinforced Autoencoder Control System (GRAACS)

Furthermore, high penetration levels in distribution grids, which connect solar PV systems, result in power quality issues like voltage fluctuations and harmonic distortion due to uncontrolled solar PV systems bring in power quality issues, such as distortions and fluctuations. There is a lack of effective solutions to deal with the complicated and diverse solar installations. To get beyond this problem, a novel Graph-Aware Reinforced Autoencoder Control System (GRAACS) was introduced, to address the critical problems when integrating solar photovoltaic systems into the power grid in terms of grid stability and power quality.

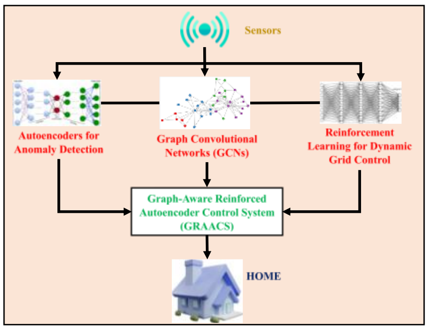


Figure 5. Architecture of proposed GRAACS

Figure 5 illustrates the architecture of proposed GRAACS. The aim of this GRAACS is to integrate solar PV systems into the modern power grid with effective management. The system shall be designed to handle numerous challenges related to grid stability, power quality-related issues, and computational efforts that arise during the real-time management of solar PV variability. It is being introduced with an objective of establishing a much more robust and flexible power grid that should be capable of integrating a higher percentage share of solar PV installations without compromising grid stability or power quality. By integrating Autoencoders for Anomaly Detection, Graph Convolutional Networks (GCNs), and Reinforcement Learning for Dynamic Grid Control, GRAACS is designed to mitigate the variability and unpredictability of solar PV generation. Therefore, GRAACS ensures the stability and reliability of the grid amidst the increasing penetration of renewable energy sources, leading toward the development of sustainable energy systems. The more details on this technique will be explained in further section.

3.6. Autoencoders for Anomaly Detection

Autoencoders are a type of neural network that offer another approach towards anomaly detection. Autoencoders are trained to learn a compressed representation of the input data in order to capture the common patterns and relationships found in the normal data. When new data is received, autoencoders identify anomalies or data points that deviate from the learned patterns.

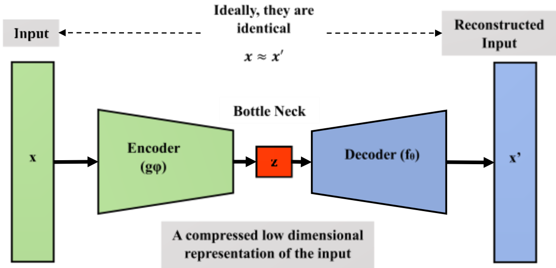


Figure 6. Structure of Autoencoders for Anomaly Detection

Figure 6 displays the basic structure of the autoencoders for anomaly detection. Autoencoders reduce input data to a lower-dimensional form and subsequently reconstruct the original data based on compressed data. During the training process, the reconstruction error (the difference between input and output) is minimized. For grid data, an autoencoder learns the normal patterns of voltage and current waveforms. Instrumentation with autoencoders, such as voltage and current waveforms measured for grid performance, results in reconstruction error over time. If the reconstruction error is variable or exhibits a spike, this change is detected by the autoencoder and indicates an anomaly. In this application, Autoencoders are implemented in real-time to monitor the ongoing input from grid performance and signal an anomaly in regards to unexpected excess voltage from uncontrolled solar PV systems. Finding such anomalous situations indicates adjustment, which the grid operator react quickly to, adjusts the setting of the inverter, or deploy a reactive power compensation device to improve power quality, such as a voltage fluctuation or harmonic distortion problems.

This supports grid stability by recognizing issues earlier to improve operation. Regarding the explanation of the application of autoencoders for abnormality detection of grid performance, an autoencoder is comprised of an encoder function f_θ and a decoder g_ϕ. Thereby, the encoder reduces the input data x, which is the voltages and current waveforms, to a smaller dimensional representation z, while the decoder reconstructs the original input from z, which is described in equation (13&14):

$$\mathrm{Encoder(z)} = \mathrm{f_\theta(x)} \tag{13}$$

$$\mathrm{Decoder}(\hat{\mathrm{x}}) = \mathrm{g_\phi(z)} = \mathrm{g_\phi}\big(\mathrm{f_\theta(x)}\big) \tag{14}$$

Where, x stands for the input data (voltage and current waveforms). z represents the compressed lower-dimensional representation. $\hat{x}$ denotes the reconstructed data. θ and ϕ represent the parameters of the encoder and decoder. The reconstruction error, $E\ (x, \hat{x})$, measures the difference between the original input x and the reconstructed output $\hat{x}$. People often calculate this using a loss function such as Mean Squared Error (MSE) which equation (15) shows:

$$\mathrm{E}\ (\mathrm{x}, \hat{\mathrm{x}}) = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \hat{\mathrm{x}}_\mathrm{i})^2 \tag{15}$$

Where, n denotes the number of elements from the input vector. x_i represents the i^{th} element actual value, and $\hat{x}_i$ is the reconstructed value. During the training phase, the autoencoder learns the normal grid's voltage and current values as patterns by minimizing $E\ (x, \hat{x})$, the reconstruction error. During operation in real time, if the reconstruction error, is significantly large, it will detect the input data x was not learned since to learn the normal patterns from the Grib, thus suspected as an anomaly. An anomaly occurs if $E\ (x, \hat{x})$ is greater than the defined threshold, ϵ, described in equation (16):

$$\mathrm{Anomaly} = \begin{cases} 1, & \text{if E (x}, \hat{\text{x}}) > \epsilon \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

Where, ϵ is the threshold value such that when the reconstruction error is above that value, it suggests an anomaly. This mathematical description gives an indication of how an autoencoder can be used in real-time to monitor and maintain stability in the grid by detecting anomalies and responding to them.

3.7. Graph Convolutional Networks (GCNs)

GCNs are a neural network architecture designed to learn from graph-structured data. This is exactly aligned with how power grids are naturally represented as graphs.

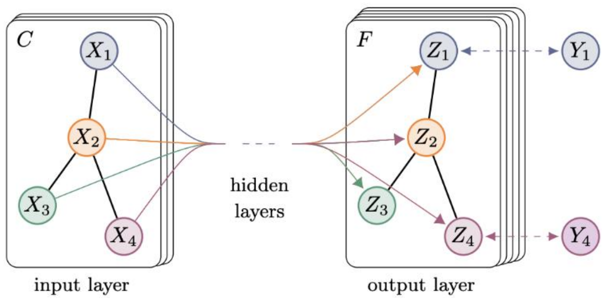


Figure 7. Structure of GCNs

The basic structure of CGNs is displayed in figure 7. GCNs facilitate information transmission along the nodes (i.e., transformers, buses, solar PV systems) in a power grid while accounting for the relationships (edges) between the nodes. Consequently, GCNs are able to represent spatial dependencies and interactions between regions of the grid. By leveraging historical performance data of the grid (e.g., voltage levels and harmonic risks across the system), GCNs is trained to predict and possibly mitigate power quality problems in distribution grids. In this manner, GCNs are able to effectively model and predict the impact of multiple solar PV systems on power quality in the distribution grid. By quantifying and capturing the relationships of differing areas of the grid, GCNs find significant value in tracking power flow and bombarding a system with disturbances. Therefore, GCNs contribute to the understanding of power flow and disturbance propagation, which supports hardware configuration optimization and device control to reduce electric potential fluctuations and harmonic distortions, and overall increase grid stability. To communicate how the GCNs model and predict the effectiveness of merging several solar PV systems on the power quality throughout distribution grid systems. It represents the power grid as a graph as expressed in equation (17):

$$G = (V, E) \tag{17}$$

V is the set of nodes (e.g., buses, transformers, solar PV systems). E is the set of edges (e.g., transmission lines, connections between grid components). Each node $v_i \in V$ have features x_i, such as voltage levels, power generation, and load demands. A GCN layer propagates the information between nodes based on the underlying connections in the graph to calculate the output feature matrix $H^{(l+1)}$ for the layer $(l + 1)$ as computed in equation (18):

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{18}$$

The adjacency matrix, denoted as $\tilde{A} = A + I$ includes self-loops which records whether nodes are connected. The diagonal degree matrix is $\tilde{D}$, which is derived from $\tilde{A}$, where $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$. The input feature matrix in layer l is $H^{(l)}$ (with $H^{(0)} = X$) and the learnable weight matrix is $W^{(l)}$ at layer l, and the activation function σ is like ReLU. The GCN model allows predicting different scenarios when various configurations of grids as well as solar PV systems are included in the relationship with power quality. The optimization problem minimizes a loss function L that is related to the power quality deviations (e.g., voltage deviations, harmonic deviations, and other deviations) as presented in a previous equation (19):

$$L = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{19}$$

y_i denotes the real power quality metric, and $\hat{y}_i$ is the prediction. Control strategies is implemented to adjust configurations on the grid or operate control devices (e.g., inverters, reactive power compensators, etc) to mitigate the issues in power quality using the GCN predictions. The adjustments will be based on the GCN models knowledge of the spatial relations and power flows within the grid.

3.8. Reinforcement Learning for Dynamic Grid Control

Reinforcement Learning (RL), a subfield of machine learning, an agent seeks to learn how to make a sequence of decisions through interaction with an environment that facilitates dynamic control of the decision making to maximize the sum of rewards under continuous adaptation and feedback.

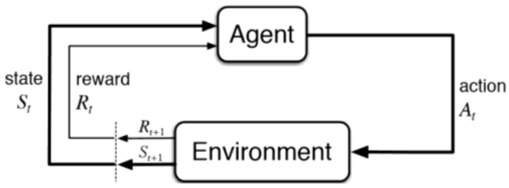


Figure 8. Structure of Reinforcement Learning for Dynamic Grid Control

Figure 8 shows the basic structure of Reinforcement Learning for Dynamic Grid Control. In the framework of power grids, a RL agent is effectively trained to exercise active management or control of grid operations in a dynamic manner. The agent receives reward signal based on how effectively the agent maintains power quality (e.g., voltage fluctuations and harmonic distortion), and the RL agent will optimize its behaviour (e.g., inverter settings or reactive power compensation devices). Like this way of approach, reinforcement learning dynamically mitigate power quality issues attributed to solar PV systems. The RL agent continues to learn and adapts to changes of the grid, improving its ability make decision to enhance stability and resilience, particularly as solar PV penetration levels increase. This form of control and optimization enables the dynamic real-time control of grid operations while learning to reduce the manual intervention level requirements, improving the reliability of the entire grid operations. As discussed previously, the framework for RL for Dynamic Grid Control, concerning determining appropriate solar PV output while managing power quality in solar PV-integrated grids for the Reward Function, is demonstrated in equation (20):

$$R_t = -(\alpha \cdot |\Delta V_t| + \beta \cdot HD_t) \tag{20}$$

R_t is the reward at time t, representing how well the RL agent is maintaining power quality. ΔV_t is the voltage fluctuation at time t. HD_t is the harmonic distortion at time t. α and β are weighting factors that determine the relative importance of minimizing voltage fluctuations and harmonic distortion. Moreover, the Policy Update is described as in equation (21):

$$\pi_{t+1}(a|s) = \pi_t(a|s) + \eta \cdot \nabla_\pi E[R_t] \quad (21)$$

$\pi_t(a|s)$ denotes the policy at time t, which represents the probability of selecting action a based on state s. η represents the learning rate $\nabla_\pi E[R_t]$ is the gradient of the expected reward, with respect to the policy, that provides the agent with a signal to update its decision-making. These equations combined express how the RL agent dynamically optimizes control actions in the grid to minimize power quality issues. By combining these algorithms, GRAACS leverages the strengths of each to address power quality issues in distribution grids with high solar PV penetration.

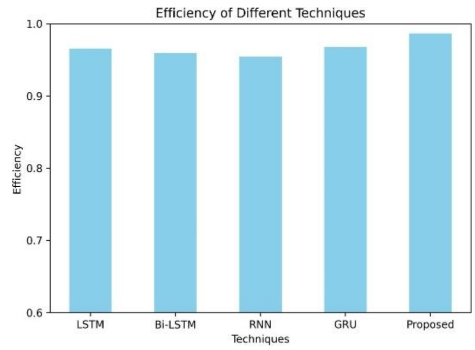
Overall, this investigation leverages advanced deep learning methods to sustainably manage grid resources associated with solar PV technologies, with a focus on sustained efficiency and reliability, and real-time management across integration challenges. The Adaptive AGRAAN is new and provides a lightweight method for solar PV forecasting and operational management of the grid with key features including neural architecture search, few-shot learning, and attention mechanics. In addition, it introduces the GRAACS to deal with grid issues about stability and power quality by deploying the autoencoder in an enterprise anomaly detection mélange, coupled with using GCNs to control a dynamic grid, for resilient and reliable integration of solar PV technology.

4. Results and Discussion

The results and discussion section of this research will demonstrate the effectiveness of the proposed deep learning models, namely AGRAAN, Adaptive Attention-Based NAS with Few-Shot Learning and GRAACS models, in promoting solar PV system integration. The analysis looks to focus on the improvement in prediction accuracy, the rapidity of achieving stable grid operations, economical computation time while performing forecasting, and model adaptability, or robustness, under varying conditions.

Figure 9 displays the comparison of efficiency of the proposed model with the existing techniques like LSTM, Bi-LSTM, RNN and GRU. The efficiency of the proposed model is 0.98, whereas the efficiency of the LSTM, Bi-LSTM, RNN and GRU is 0.96, 0.95, 0.95 and 0.96. There is a significant improvement in the proposed model. The proposed model demonstrates better efficiency which means the ability to manage intricate patterns is more superior productivity which in turn suggests improved precision and dependability.

As shown in figure 10, a comparison of the F1-Score of this model with that of existing techniques such as LSTM, Bi-LSTM, RNN and GRU were made. In specific, their respective F1-Scores are 0.95, 0.94, 0.93 and 0.94 respectively while that of proposed model is 0.97. This indicates that they proposed design is a great stride forward. The high F1-Score of the proposed model affirms that there is better precision and recall trade-off hence giving out more dependable and accurate results.



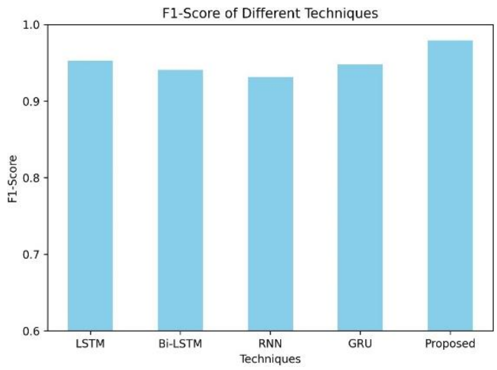


Figure 9. Efficiency of the proposed model **Figure 10.** F1-Score of the proposed model

This is graphically represented in figure 11 that compares the MAEs of the proposed model with MAE comparisons made on other methods such as LSTM, Bi-LSTM, RNN and GRU. Pleasantly placed: their relative MAEs were 0.27, 0.29, 0.38 and 0.24 respectively against 0.11 for the model proposed here. Clearly, the design they've given us is a great step forward. In less technical terms, a lower MAE indicates that the proposed model has better predictive capability and decreases mistakes much better than previous methods.

From the comparison of proposed model MAPEs with alternative methods' MAPEs like (LSTM, Bi-LSTM, RNN and GRU) are seen in figure 12. In this position: their corresponding MAPEs were respectively 7.4x1014, 6.9x1014, 9.5x1014 and 4.9x1014 compared to 2.5x1014 for the proposed model. It is easily seen that the design they offered is much better than any other one. The proposed model has significantly lower MAPE resulting in a more accurate estimation of relative errors which demonstrates an evident progress from past techniques.

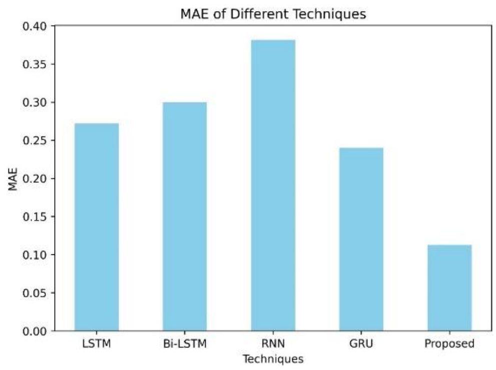


Figure 11. MAE of the proposed model

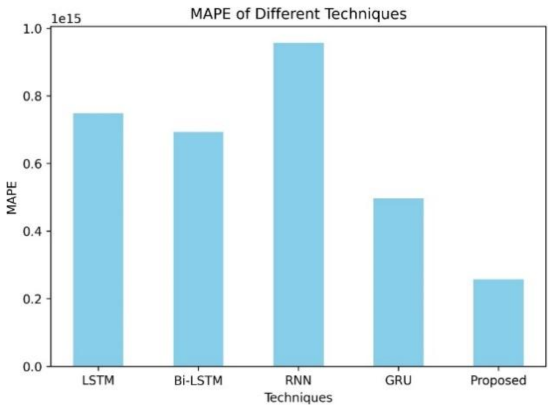


Figure 12. MAPE of the proposed model

According to figure 13, a comparison between the proposed MCC and that obtained by several methods, such as LSTM, Bi-LSTM, RNN and GRU has been made. In this case, their individual MCCs were 0.95, 0.95, 0.94 and 0.95 respectively as opposed to 0.98 for the proposed model. The clear superiority of their design compared to all others is easily noticeable. The proposed model has a higher MCC implying better capacity in classification altogether which makes it have an improved balance between true positive and true negative values.

The results for memory usage (in MB) of some techniques, such as LSTM, Bi-LSTM, RNN and GRU are compared to the proposed model's Memory used (MB) in figure 14. The individual memory consumed (MB) by these methods were 690.3258MB, 611.0326MB, 670.2568MB and 690.255MB respectively against the memory consumed by the proposed model which was 520.6545MB. Its design has a clearer-cut superiority over any other competing design. This indicates that lower memory consumption by existing models proves their inefficiency hence making the proposed model more efficient and economizing on computing resources required for operation as opposed to existing models.

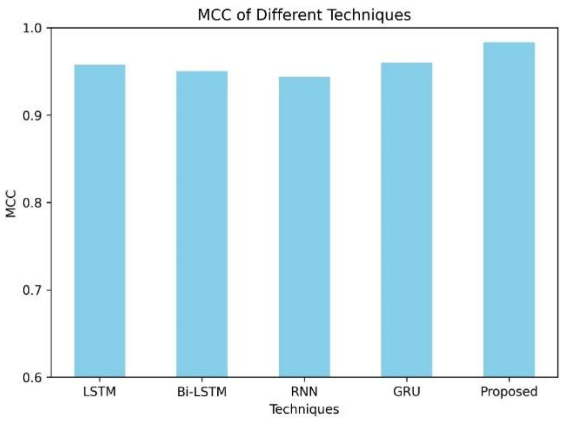


Figure 13. MCC of the proposed model

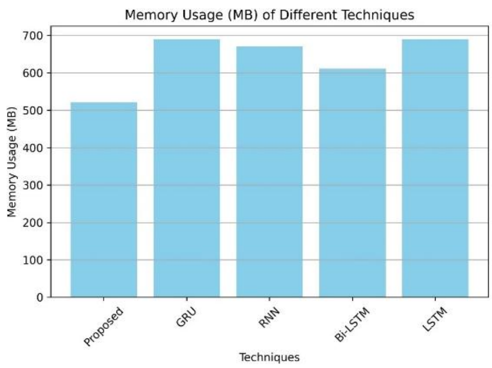


Figure 14. Memory used (MB) of the proposed model

In comparison with MSE findings for different approaches (LSTM, Bi-LSTM, RNN, and GRU) including the proposed model, its MSE is plotted in figure 15. The MSE of LSTM was 2.87; Bi-LSTM is 3.27; RNN is 4.52; GRU is 2.58 as opposed to 1.29 for the proposed model which gives it a significant design advantage over competing alternatives. Thus, this design has lower MSE than any of these other models hence demonstrating higher accuracy and effectiveness through lesser prediction errors.

In figure 16 its Precision plotted against other techniques results of precision (LSTM, Bi-LSTM, RNN and GRU) including proposed model. These values with 0.93 for LSTM, 0.92 for Bi-LSTM, 0.91 for RNN and 0.93 for GRU compared with 0.97 proposed model as having a significant design edge over competing alternative. The proposed model's higher Precision underscores its capacity to accurately detect relevant cases thus making it more effective than other approaches.

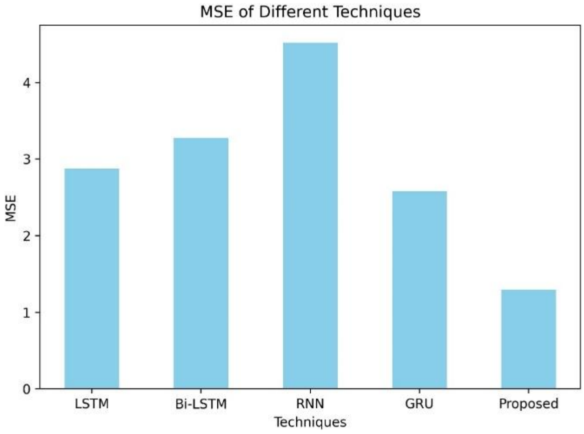


Figure 15. MSE of the proposed model

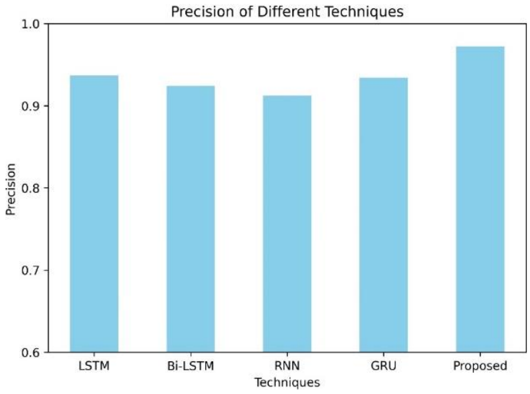


Figure 16. Precision of the proposed model

The R2 results for models (LSTM, Bi-LSTM, RNN, and GRU) compared with the proposed model are shown in figure 17. These values are LSTM: 0.93, Bi-LSTM: 0.92, RNN: 0.89 and GRU: 0.93 while the proposed model's value for R2 is 0.96 showing that it has a significant design edge over its competitors. A higher R2 of this model implies that it fits better into the data as well as having more predictive precision and also being more explanatory than the others do.

Recall results for the models (LSTM, Bi-LSTM, RNN, and GRU) are shown in figure 18 and compared to the proposed model. These values are as follows: LSTM gets 0.97, Bi-LSTM gets 0.95, RNN gets 0.95 and GRU gets 0.96. The proposed model has Recall value of 0.98 which is a significant design advantage over its competitors'. Therefore, the proposed model's superior recall implies that it identifies all relevant instances better thus it ensures superior completeness and fewer missed detections than other models.

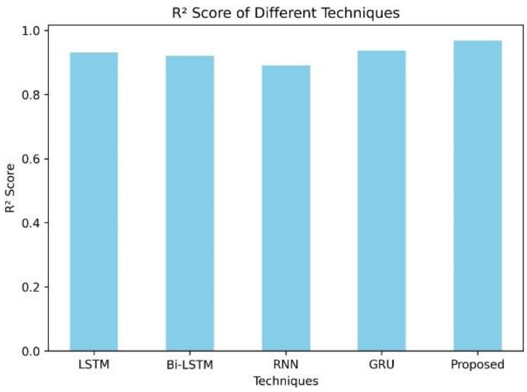


Figure 17. R2 of the proposed model.

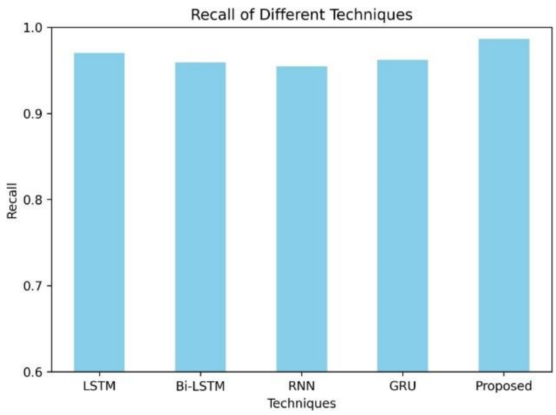


Figure 18. Recall of the proposed model.

The results of RMSE with respect to models (LSTM, Bi-LSTM, RNN and GRU) are illustrated in figure 19 against those of the model proposed in this paper. The RMSE values for LSTM, Bi-LSTM, RNN and GRU are as follows; 1.69, 1.81, 2.12 and 1.42 respectively for each model respectively whereas the proposed model has an RMSE of 1.13 making it a significant design advantage over its competitors. Hence this indicates that the proposed model is more accurate and reliable than others since it predicts better with relatively lower errors on average.

The training time in seconds for the models (LSTM, Bi-LSTM, RNN and GRU) shown in figure 20 is compared to that of the model presented here. The LSTM training times, Bi-LSTM training times, RNN training times and GRU training times are 19.015 sec, 19.32654 sec, 21.645 sec and 20.89223 sec respectively. But the proposed model has a

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distinct advantage in design over its competing counterparts by requiring only 15.35 sec for the same task. This means that the proposed model is more efficient than others because it is developed quickly and iterated faster than others do already existing ones with longer periods of time required for completion on them. Overall, the AGRAAN, Adaptive Attention-Based NAS with Few Shots Learning, and GRAACS proposed deep learning models show optimal results when integrating solar PV systems. The existing methods (LSTM, Bi-LSTM, RNN and GRU) have been outperformed by the model's efficiency (0.98 vs. 0.96-0.95), F1-Score (0.97 vs. 0.95-0.93), MAE (0.11 vs. 0.27-0.24), and MAPE (2.5 × 1014 vs. 7.4 × 1014−4.9× 1014). In terms of memory usage (520.6545 MB vs 6903258-6110326MB), MSE (1.29 vs 4.52-2.58), Precision (0.97 vs 0.93-0.91), R^2 (0.96 vs 0.93-0.89) as well as Recall (0.98 vs 0.97-0.95) the proposed models did well but had lower RMSE (1.13 vs 2.12-1.42) and faster time of training (15.35 sec vs 21.645-19.015 sec).

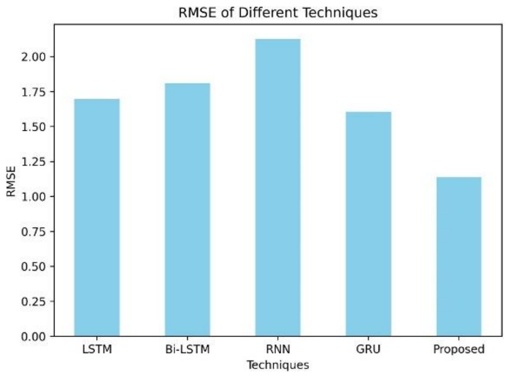

Figure 19. RMSE of the proposed model.

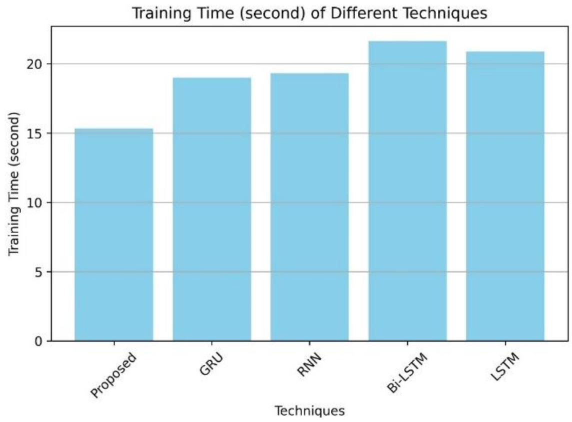

Figure 20. Training time (second) of the proposed model.

5. Conclusion

Regarding the primary issues high computational demands, a new innovative technique called AGRAAN was implemented in this approach. Additionally, to solve the variability issues in the power grids of solar PV installations, a novel Adaptive Attention-Based NAS with Few-Shot Learning has been introduced, which optimizes neural networks for real-time solar PV variability to improve forecasting, adaptability, cost, and scalability. This technique is the integration of the existing algorithms like Neural Architecture Search (NAS) for optimization purpose, which accurately predict how solar PV production will vary over short periods of time, Few-Shot Learning for adaptability purpose which helps in making predictions in specific settings where data is rare and Attention Mechanisms in Time-Series Forecasting for focusing purpose in which enhance real-time variability management while supporting better grid stability and response atmospheric parameters. Moreover, to get beyond the instability problems, a novel GRAACS was introduced, which detects voltage fluctuations and harmonic distortion, which are further mitigated by advanced detection, spatial analysis, and adaptive real-time control in solar PV grids. This is the combined strengths of existing algorithms like Autoencoders for Anomaly Detection for detection purpose which allows for real-time performance and abnormality detection from solar PV systems, enabling grid operators to isolate and quickly correct power quality issues with mitigation actions like inverter adjustments, GCNs for prediction purpose which models and predicts the impact of multiple solar PV systems on power quality to assure that grid configurations are optimized to effectively reduce voltage fluctuations and harmonic distortions and Reinforcement Learning for Dynamic Grid Control for optimization purpose which provides dynamic adjustment of grid operation in mitigating solar PV-induced power quality issues through continuous learning and adaptation for real-time optimization. The results obtained from the experimental works have been shown to progress highly in terms of efficiency, 0.98; F1-score, 0.97; and MAE, 0.11, as opposed to existing techniques. It also portrayed better precision, recall, and faster training times 0.97, 0.98, and 15.35 sec, respectively, thereby giving proof of the effectiveness and efficiency of the models in the integration of solar PV systems. Future work will explore real-world deployment and scalability of the integrated AGRAAN and GRAACS frameworks while enhancing computational efficiency, interpretability, and robustness in hybrid renewable grid environments.

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6. Declarations

6.1. Author Contributions

Conceptualization: S.P., S.D., and M.B.; Methodology: S.D.; Software: S.P.; Validation: S.P., S.D., and M.B.; Formal Analysis: S.P., S.D., and M.B.; Investigation: S.P.; Resources: S.D.; Data Curation: S.D.; Writing Original Draft Preparation: S.P., S.D., and M.B.; Writing Review and Editing: S.D., S.P., and M.B.; Visualization: S.P. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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