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Adaptive Control of PV-Integrated Power Grids Using KNN-Smote-GCN And Mpc Techniques

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As the global energy crisis intensifies, the integration of renewable energy—particularly photovoltaic (PV) systems—has become vital for achieving a sustainable and resilient power infrastructure. This study focuses on dynamic modeling and efficient control of grid-connected PV systems to enhance power quality and system reliability. An adaptive PI controller is employed for voltage regulation, with a maximum power point tracking (MPPT) method ensuring optimal energy harvesting. A DC-DC boost converter and a three-phase PWM inverter are incorporated, with MATLAB used for simulation. The proposed approach integrates Model Predictive Control (MPC) with Graph Convolutional Networks (GCN) to manage grid instability and improve energy efficiency. A novel KNN-SMOTE-GCN algorithm is developed to mitigate voltage distortion, harmonic currents, and power fluctuations. The system replicates the behavior of traditional generators under disturbances, promoting renewable integration without compromising stability. Key performance metrics such as voltage deviation, reactive power fluctuation, power loss, and total harmonic distortion (THD) are analyzed.

Povzetek: Integrirani KNN-SMOTE-GCN in MPC izboljšata stabilnost PV-omrežij z natančnim MPPT, učinkovitim nadzorom napetosti ter zmanjšanjem izgub, nihanja jalove moči in THD. Metoda poveča kakovost energije in zanesljivost šibkih omrežij z visoko penetracijo PV.

1 Introduction

The reckless use of hydrocarbons and nuclear power threatens environmental safety and causes significant pollution. The truth of this energy source is prompting a global movement toward renewable energy sources that are less harmful to the environment, including as wind power, PV, and others. Distributed power generating systems that employ renewable energy sources have garnered significant interest due to the current focus on clean power generation [1], [2], [3]. Recent advances in photovoltaic technology have led to the rapid adoption of renewable energy production based on solar PV by both commercial and residential sectors. Reduced main power system load, maximum savings, and reactive power support are just a few of the benefits that the distribution grid may reap from integrating distributed solar PV generating plants [4], [5]. electricity quality and dependability are both enhanced by solar PV electricity, which lessens the strain on the central grid. The energy quality usually drops as the use of non-linear loads increases. It is also well known that most non-linear loads that produce more complex harmonics and demand reactive power are electronic power equipment. This action causes voltage distortion, which impacts all subsequent loads linked to the identical PCC. Optimal performance of solar photovoltaic inverters is hindered by the unpredictability of sun irradiation [6], [7]. Two examples of supplementary services that the inverter's extra capacity may offer are reducing source current harmonics while adjusting reactive load power. When it comes to PV-integrated systems, MPPT is a go-to for reducing harmonics. One method for reducing PV system grid current harmonics is the adaptive P&O (perturb and observation) MPPT algorithm, which incorporates sliding mode control [8], [9]. The goal of auxiliary regulation is to maintain grid stability by modifying power system characteristics in response to imbalances, fluctuations, and disruptions. The grid, however, functions within reasonable bounds and adapts efficiently to shifts in both generation and demand [10], [11]. Controlling the grid frequency entails modifying either electricity production or consumption to keep it within predetermined boundaries. Ensures that electrical equipment continue to function correctly by keeping voltage levels within certain limits. Optimizes system performance by balancing the production and consumption of both reactive and active electricity. More conventional approaches, such as DL, Machine Learning, etc [12]. These systems are often studied for their possible use in power system optimization, control performance, and forecasting. Due to a lack of sophisticated automation infrastructure, many system operations are being performed with modest degrees of automation at the time. AI is expected to play a significant role in the future power system, according to several studies, technical papers, and case studies [13], [14]. This is because AI will introduce state-of-the-art techniques of system optimization while simultaneously decreasing the need for human participation. Research on AI for grid system power flow optimization is now at a premium. The auxiliary services that help to reduce frequency variations are crucial to the reliability of ac power networks. Large synchronous generators' electromechanical inertia is the only available resource for absorbing frequencies disturbances on subsecond time scales at the moment. This means that switching from traditional thermal power plants to NREs, which are inertialess, puts grid stability at risk from things like unexpected power production outages. Grids with high penetrations of NREs may suffer from electromechanical inertia, which may disrupt system stability. To address this, virtual synchronous generators have been suggested, which mimic traditional generators. In this paper, we provide a new method of controlling virtual synchronous generators that uses a configurable time scale to reduce the supplied inertia, which is large at short intervals to absorb faults as effectively as traditional generators but sets in motion coherent frequency oscillations when it doesn't [15], [16]. We test how well our adaptive-inertia approach handles large-scale transmission networks that experience unexpected power outages. It is more stable than earlier proposed methods and consistently outperforms traditional electromechanical inertia. The numerical simulations demonstrate that the quasioptimal placement of adaptive-inertia devices enhances the damping of interarea oscillations and effectively absorbs local faults. In future low-inertia power grids that have significant penetrations of NREs, our findings demonstrate that the suggested adaptive-inertia control system is a great way to improve grid stability [17], [18], [19], [20].

1.1 Problem statement

In today's world, contemporary power systems are complemented with large-scale renewable energy systems, allowing for more efficient operations. Accurate energy production and efficient control systems to manage while guarantee a reliable power supply are also necessary for optimum power systems. However, there is a degree of uncertainty due to the high electrical consumption and the sporadic balance of supply. Also, traditional power sources aren't practical for such a difficult job, and they drive up energy prices.

The next step was to improve electrical distribution networks' power quality by using an optimization approach. It employs a hybrid design that incorporates shunt and series compensators to address voltage drops, harmonics, and imbalance, among other power quality concerns. Afterwards, MPPT was used to derive the greatest amount of power from the grid system. Controller for MPC to ascertain the system's overall stability and performance. In addition, the model was tested on the MATLAB platform and its reliability was assessed by measuring voltage variation, reactive power fluctuations, grid current, and THD.

1.2 Motivation

Many issues, including power quality, stability, dependability, and supply management, may arise as a result of the increasing need for big power grid-connected systems. In addition, the total system performance might be negatively impacted by power quality concerns as a result of variations. It is possible for there to be an imbalance in the power demand and generation frequency fluctuations. Next, problems with the power factor, such as a low power factor, might cause the power distribution system to lose more power and increase energy usage. Voltage instability is the root cause of both linear and non-linear problems. Voltage regulation may be subpar due to the persistent use of insufficient control mechanisms in power grid systems. Ensuring the stability and operation of big power networks also relies heavily on rules and norms that specify acceptable power quality values. As a result, grid systems need an intelligent auxiliary regulatory technology that can effectively lessen the burdens on them.

1.3 Contributions

Despite the paper's focus on intelligent real-time power grid regulation and control, no mention of research into building the comprehensive functional foundation of a dispatching intelligent assistant driving network is made. The study and evaluation of real-time regulation and control business aims to explore fresh artificial intelligence application methods for various business processes, as well as the principle and implementation characteristics of a grid-assisted control system based on AI thinking and decision-making in regulation and control operations. In order to achieve the shift from empirical to intelligent control and enhance the degree of control over the power grid, we provide solutions to raise the bar for artificial intelligence in terms of both interaction and performance. In order to achieve maximum power generation, it is necessary to control the working point of photovoltaic panels. For this regulation procedure to be successful,

there are two primary components that are required: an MPPT algorithm that serves as the reference for the MPP, and a voltage controller that guarantees a steady functioning at the MPP.
One of the most significant benefits of adopting MPC is that it has the ability to simplify the process of developing a variety of controllers while also working to accommodate system limits within its formulation. In addition, the introduction of KNN-SMOTE-GCN as a user-friendly optimization approach is suggested in this study as a means of enhancing the cost function of the MPC controller.
This research work is structured as follows: Section 2 describes the research articles that were relevant to the framework that was developed; Section 3 describes the problem statements; Section 4 explains the proposed hybrid framework; Section 5 analyzes the results of the methodology that was proposed; and Section 6 describes the research conclusion.

2 Related work

Experts from [21] grid operators use neuro-fuzzy logic for dynamic reactive power adjustment. The energy storage system may also be effectively managed using that logic. After that, SP UPQC was used to improve the electrical distribution networks' power quality. It employs a hybrid design that incorporates shunt and series compensators to address voltage drops, harmonics, and imbalance, among other power quality concerns. Afterwards, maximum power point tracking was used to derive the greatest amount of power from the electricity network. Controller for Model Predictive Control to ascertain the system's overall stability and performance. In addition, the model was tested on the MATLAB platform and its reliability was assessed by measuring voltage variation, grid current, reactive power fluctuations, and Total Harmonic Distortion.
Enhancing the effectiveness of section control of large power grid, altering the traditional experience-led dispatching mode, and improving the intrinsic safety level of the power grid are all goals of the experimental team in [22]. They study intelligent section auxiliary decision-making algorithms in depth and build a new intelligent dispatching structure framework of the power grid using deep learning and simulation environments. To build a more realistic simulation of the power grid's dynamic characteristics under varied operating circumstances, an environment that is suited for the upcoming AC-DC hybrid big power grid is first built. Secondly, a scheduling agent that takes into account the power grid's characteristics and the dispatcher's behavior is researched using the power grid's historical operation data and the dispatcher's real control data. Finally, to address the issues of poor regulation speed, complex regulation decision-making, and inadequate technical support ability, authors study the technology that generates and verifies strategies for multi-dimensional scheduling agents using deep reinforcement learning. In addition to providing solid technical support for power grid operation, that research may enhance the accuracy and effectiveness of section dispatching decision-making, optimize the section control strategy continually, and more.
According to [23], when a problem occurs, the generator network determines the unit output plan using the combined wind, light, and electrical demand data from a northwest area of China. A specialized system generation fault recovery strategy is developed for that grid fault using data on actual power load while actual renewable energy output before and after the fault. The strategy aims to minimize the cost of system power generation while considering the constraints of secure operation of the system. It turns out that the expert system's fault recovery method is much different from the one used in the early stages of training, and that the error value is very high. After a generative adversarial network is fully trained, it can approach the fault recovery expert system with an auxiliary decision-making scheme that works in different situations with different loads and new energy outputs, and it can keep the error between the two schemes to less than 5%. Results from studies examining power grid fault recovery strategies using models of generative adversarial imitation learning networks demonstrate the force control system's capacity for autonomous and secure fault recovery.
With the goal of conducting real-time tracking on the operating state of the power grid, eliminating potential safety hazards, and upgrading the power grid from "manual analysis" scheduling to "intelligent analysis" scheduling, the authors of [24] propose an integrated framework to aid decision-making of online accident processing using large power grids. The study covers five aspects: integrated information support system, aid decision-making afterwards, risk perception in grow, online fault diagnosis, and visual display.
The writers of the cited work, [25] an online trend analysis technology with a functioning mode arrangement for large power grids is suggested, drawing on references to the growth of intelligent dispatching support systems and their dynamic security assessment technologies, in light of the growing importance of grid dispatching operations in understanding future state security changes. Estimated power flow in the future is based on the power grid's present operating mode, online stability conclusion, data from fresh energy and load forecasts, dispatch scheduling, and dispatch operation adjustment. The auxiliary decision-making approach for control allows for fast assessment of future security situations and trends. With the use of that technology, the power grids of Heilongjiang and Central China have been able to transition from empirical to intelligent control, and precontrol techniques for

complicated power grid dispatching operations have received technological support.

The tiny sensor sample unit, energy metering device, communication unit, protection control device, performance evaluation unit, etc. were all combined by the experimenters of [26]. In conjunction with the transformer, keeping its original dimensions and construction. It is possible to analyze the measured data locally, allowing for an intelligent and transparent observation of the performance indicators of the transformer. Simultaneously, it can accomplish intelligent monitoring, reduce energy consumption and save energy, and aid in the creation of new power systems without uploading a mountain of normal and abnormal data.

Using deep reinforcement learning, the authors of [27] provides an auxiliary control method for large-scale power grid segments. An intelligent agent for power grid section control is built using the Deep Deterministic Policy Gradient algorithm. That agent provides real-time control methods in complex power grid settings, taking into account both the safety and economics of power grid operations. That justifies the proposal of a two-stage optimization approach that takes sensitivity into account. When operators are unable to remove the section restriction via real-time control, they offer them with the optimum market intervention strategy. At last, the efficacy of market intervention plans and real-time control mechanisms are tested via case studies. The methodology presented in that study improves the system's economy by lowering the clearing price through an average of 1.2% while the average adjustment amount through 37.6% under various section limits resulting from power generation components participating in the market, as compared to the current rules.

The authors of [28] looking at the power grid from a knowledge graph perspective, researchers were able to develop a functional framework for an intelligent evaluator that could assess static stability, make decisions based on that evaluation, and be an all-around smart algorithm. That evaluator took into account the stability state evaluation index while optimization control strategy data from various power grid operation scenarios. The implementation of a visual evaluation tool for large-scale power grid static stability was made possible with the introduction of technology for knowledge graph automation engines. To demonstrate the efficacy of the suggested approach, an example using a real-world electricity system is provided. Regulatory and control operators may benefit from the study's findings by better understanding the current state of operations and making more informed decisions about the power system. Explorationally, it may be useful for enhancing the building of online intelligent active security defense structures on big power grids.

3 PV generated system integrated to weak grid

The basic architecture of a three-phase grid-connected double-stage solar power plant is shown in Figure 1. The integration of solar electricity into the electrical grid is achieved via the employment of this sort of technology, which guarantees effective power conversion and maintains grid stability. To generate and transmit electricity from the solar PV array to the unreliable utility grid, the system relies on a number of moving parts, all of which contribute in different ways. The PV array generates the majority of the system's renewable electricity. It relies on a network of solar panels to generate DC power from sunlight. The PV array's power production is directly related to the amount of solar irradiation and temperature that it can operate at. Maximizing the conversion of solar energy into grid-ready alternating current electricity is the system's primary objective. To get the most power out of the solar PV system, the DC-DC boost converter is an absolute must. For maximum efficiency in power conversion, it raises the DC voltage produced by the PV array until it is equal to or greater than the DC-link voltage. In order to keep the PV array running at its optimum power point no matter what happens to the weather or irradiance, the boost converter works using a MPPT algorithm. An MPPT method known as Perturb along with Observe is used to optimize the amount of energy harvested by the PV array. One of the most popular ways to increase the output of solar PV systems is by using this algorithm.

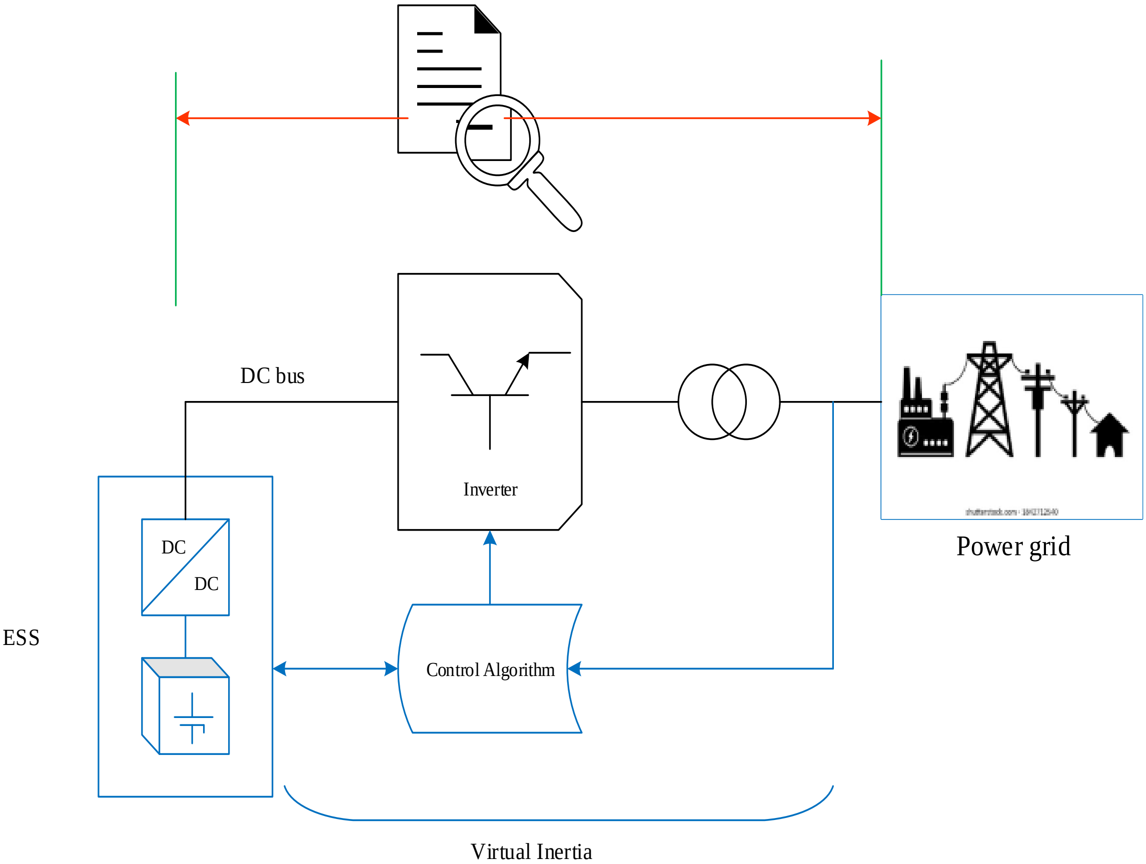

Figure 1: Auxiliary power control in large power grid

It works by monitoring the change in power output and making adjustments to the operating voltage of the PV array at regular intervals. When the power goes up, the adjustment stays the same; when it goes down, it goes in the other way. The technology is able to maintain optimal performance regardless of environmental changes because of this iterative procedure that continually monitors the PV array's MPP. By responding in real-time to variations in temperature and irradiance, the P&O MPPT algorithm keeps the boost converter operating at the ideal voltage input from the PV array. In areas where the amount of sunshine varies throughout the day, the efficiency of the solar PV system depends on this capability to monitor the MPP under changing circumstances.

3.1 PV array modelling

To enhance the voltage or current level, the PV panel uses numerous modules linked in series or parallel, accordingly. A current source, two types of resistance (series and shunt), with an antiparallel diode make up the equivalent circuit of a PV cell, as shown in Figure 2. The current source (I_s) is expressed by de following equation:

$$I_s = \left(\frac{G}{G_{ref}}\right)\left(I_{s\_ref} + K_{sc} \cdot (T - T_{ref})\right) \quad (1)$$

where irradiance (G) and ambient temperature (T) are the two variables. The coefficient of short-circuiting current is denoted as K_{sc}. The following are the current, irradiation, as well as temperature under typical conditions: I_{s_ref}, G_{ref} and T_{ref}. The current changes with irradiation and temperature change, as shown in Eq. (1); yet, the I_{sat} fluctuation in temperature is the only determinant of current. In accordance with Kirchhoff's law, the PV panel's output current (v_{pv}) is given through:

$$I_{pv} = I_s - I_d - I_{shu} \quad (2)$$

Yes, it means we can:

$$I_{pv} = I_s - I_{sat}\left[exp\left(\frac{q\left(v_{pv}+(I_{pv}*R_{Ser})\right)}{nkT}\right) - 1\right] - \frac{V_{pv}+(I_{pv}*R_{Ser})}{R_{shu}} \quad (3)$$

With:

$$I_d = I_{sat}\left[exp\left(\frac{q\left(v_{pv}+(I_{pv}*R_{Ser})\right)}{nkT}\right) - 1\right] \quad (4)$$

And:

$$I_{shu} = \frac{V_{pv}+(I_{pv}*R_{Ser})}{R_{shu}} \quad (5)$$

3.2 DC-DC converter

Here is one way to express the transfer function of the boost converter:

$$v_m = \frac{1}{1-D} v_{pv} \quad (6)$$

The relationship between the average currents flowing into and out of an electrical device may be expressed as follows:

$$I_{pv} = \frac{1}{1-D} I_{dc} \quad (7)$$

The equation for the DC bus may be written as:

$$\frac{dv_{dc}}{dt} = \frac{1}{C}(I_{dc} - I_{inv}) \quad (8)$$

3.3 DC-AC inverter

It is possible to transform DC electricity into AC voltage with the frequency and amplitude of our choice thanks to the inverter, the adaptation step. The inverter control makes it possible to inject higher-quality currents and powers (P,Q) into the grid. The input/output inverter voltage relationship is defined as:

$$\begin{cases} v_{an} = (S_1 - S_2)v_{dc} \\ v_{bn} = (S_2 - S_3)v_{dc} \\ v_{cn} = (S_3 - S_1)v_{dc} \end{cases}$$
$$\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \frac{v_{dc}}{3} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix} \quad (9)$$

where v_{dc} is the DC voltage, $v_{in}(i = a, b, c)$ and $S_j(j = 1,2,3)$ consist of alternating current voltages and signals indicating the current state of the switches. Here is the equation for grid voltages:

$$\begin{bmatrix} v_{ga} \\ v_{gb} \\ v_{gc} \end{bmatrix} = \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} + R \begin{bmatrix} I_{ga} \\ I_{gb} \\ I_{gc} \end{bmatrix} + L \frac{d}{dt} \begin{bmatrix} I_{ga} \\ I_{gb} \\ I_{gc} \end{bmatrix} \quad (10)$$

The goal of studying and realizing the decoupling among the active (P) with reactive (Q) capabilities was to regulate them independently. If we want a fair system, we can just put down the powers P_g and Q_g as follows:

$$\begin{cases} P_g = \frac{3}{2}(v_{gd}I_{gd} + v_{gq}I_{gq}) \\ Q_g = \frac{3}{2}(\mathrm{v_{gq}I_{gd}} - \mathrm{v_{gd}I_{gq}}) \end{cases} \quad (11)$$

Indeed, we can write:

$$\begin{cases} \mathrm{P_g} = \frac{3}{2}\mathrm{v_{gd}I_{gd}} \\ \mathrm{Q_g} = -\frac{3}{2}\mathrm{v_{gd}I_{gq}}) \end{cases} \quad (12)$$

where $\mathrm{v_{gdq}}$ as well as $\mathrm{I_{gdq}}$, which stands for grid current.

3.4 Normalization

The data were standardized to ensure that the model's accuracy was unaffected by dimensions. The min-max scaling approach was used for normalization in this research.

$$\hat{x} = \frac{x - min(x)}{max(x) - min(x)} \quad (13)$$

where $\hat{x}$ stands for the value of the normalized property. The function min(x) finds the lowest value in the values of the attributes while max(x) finds the highest value.

3.5 Missing value completion

One approach that uses nearby data points is KNN (K-Nearest Neighbors) interpolation. The goal of this technique is to estimate the target point's value by comparing it to the values of the K data points that are known to be the closest to it. For KNN interpolation, the fundamental procedures are these:

Choose the K-value: Choose the optimal K-size by determining its value, often using cross-validation.

Determine Distance: Find the total distance in geometric units between the current location and all other known locations. This is the formula for the distance in geometric units:

$$l(x_l, x_f) = \sqrt{\sum_{m=1}^{M} (x_{l,m} - x_{l,m})^2} \quad (14)$$

where x_i and x_j constitute data points, with M serving as the data dimension.

How to Determine the K-Nearest Neighbours: choose the K known points of data that are most closely located to the desired location.

Weighted averaging: Give each of your K neighbors a weight that is inversely proportionate to their distance from you. The formula for the weighted average interpolation for the K closest neighbors is

$$\hat{y} = \frac{\sum_{k=1}^{K} w_k y_k}{\sum_{k=1}^{K} w_k} \quad (15)$$

where y_k w_k is the weight that defines the distance from the location to be interpolated, and is often specified as the opposite proportion of the distance, and is the value of the k-th neighbour:

$$w_k = \frac{1}{d_k} \quad (16)$$

3.6 Deal with unbalanced data

In classification tasks, when minority samples are oversampled, an interpolation approach called Synthetic Minority Oversampling Technique (SMOTE) is used to address imbalanced datasets. By augmenting the dataset's diversity via the synthesis of fresh minority samples, SMOTE boosts the classifier's performance. The detailed procedures are these:

Pick a Representative Sample: Pick a representative sample at random from the minority group.

Determine the sample's k closest neighbors by using a distance measure.

Create a fresh sample by using the following formula to synthesize a neighbor from among these k neighbors at random:

$$\text{new\_sample} = x_1 + \lambda(x_1 - x_1) \quad (17)$$

3.7 Maximum power point tracking (MPPT)

The DC-DC boost converter controls the output of PV cells, which is one of its dual functions. As a result, MPPT is simplified and the output voltage is reliably controlled. This study combines a DC-to-DC converter with the widely known MPPT algorithm to optimize power extraction from PV panels. The operating point must be dynamically changed to the Maximum Power Point in order to accommodate changing weather conditions. The low cost and user-friendliness of the MPC algorithm led to its selection for MPPT. The MPC algorithm tracks the PV array's current and voltage down to the microsecond in order to foretell how a voltage modification will play out. This approach may be more resource intensive, but it can adapt to new conditions very fast. A little amount of energy can be saved in that gadget for use in seconds, and its performance is assessed by comparing the discharged and charged powers of the device. At all times, the following equation (4) describes how the charging and discharge rates of the constraints are combined with the battery efficiency.

$$W'_{ess}(n) = W'_{ess}(n-1) + \alpha_c p'_c \Delta n - \frac{1}{\alpha_d} p'_d \Delta n$$
$$\begin{cases} W'_{ess} \leq W'_{ess}(n) \leq W'_{ess} \cdot \max \\ p'_c(n) \leq p'_{c\cdot\max} \\ p'_d \leq p'_{d\cdot\max} \end{cases} \quad (18)$$

Where, W'_{ess} The energy storage limits are represented by p'_c, the charging power is p'_d, and the battery efficiency while charging and discharging is α_c.

3.8 Cost function

Using three crucial factors, including 1) the energy and discharging rate of each grid system, 2) the degradation cost of the battery and the discharge rate, and 3) the operation cost of other activities such service chargers and cable wear, we need to build the net cost function of the j^"th" grid system. First, use the following equation (5) to express the grid system discharge rate.

$$U_j\lfloor C'_j(n) \rfloor = p'(n) C'_j(n) \quad (19)$$

where $p'(n)$ represents the unit pricing with the grid aggregator at time n, and c'_j(n stands for the discharge rate of each network grid at that specific time n. In this case, the degree of the generated aggregator grid system is shown by the increased energy wasted at the grid system. As a result, the grid power plant facilitates degradation cost in order to fulfill the particular demand at the grid system's discharge point. Equation (6) also allows for the modeling of the deterioration cost using a quadratic function.

$$d'_j[c'_j(n)] = \delta_j c'_j(n)^2 + \mu_j c'_j(n) + \lambda_i \quad (20)$$

Where, δ_j, μ_j and λ_i represents the degradation cost function and is represented by operational cost parameters $d'_j \mid c'_j(n)]$. Because of the limited integration between the operating cost parameters and the grid system's discharging rate, the constant value here must be associated with the grid system's discharge rate. However, using eqn. (21) in the following context, the cost function's simplicity is related:

$$f'_j[c'(n), p'(n)] = d'_j[c'(n)] + o'_j - U_j \mid C'_j(n)] \quad (21)$$

Where, o'_j is the formula for the lumped cost. Here, power is supplied by the grid at a net cost rate according to the electricity pricing unit with either an off-peak or peak-time tariff. Not to mention that the fixed price unit diverges from the original cost function.

3.9 Design of MPC

An extensive evaluation of the reference grid currents is carried out, taking into consideration various factors such as the presence of nonlinear loads at the Point of Common Coupling, regulation of the DC link voltage, and dynamic variations in PV power. This reference current is fed into the MPC controller, which then calculates the quantity of switching pulses required for optimum functioning. Considering the dynamic changes in PV power, ensuring stable control of the DC link voltage, while tolerating nonlinear loads at the PCC allow the system to efficiently supply reference grid currents that sustain efficient operation. The MPC controller enhances the system's general efficiency and stability by using these currents to identify the optimum switching pulses. As a result, the following equations (8), (9), (10), (11), define the key function of the charging station's net cost function in regards to multi-objective optimization problems.

$$\begin{aligned} &\min C_j(n) = \textstyle\sum_{j \in T(n)} s_j \mid C_j(n) + G(n)] \\ &C_j(n) = C_j(n) \forall j \neq i \in T(n) \\ &C^j_{min} \leq C_j(n) \leq C^j_{min} \forall j \in T(n) \\ &SOC^j_{min} \leq SOC_j(n) \leq 100\% \forall j \in T(n) \end{aligned} \quad (22)$$

Where, $C_j(n)$ represents the cost function of a grid system charging station, and is depicted as the minimization of the net cost function for every grid system charging stations,

$\sum_{j \in T(n)}$ appears as the energy cost function for the jth user over the time interval t. Additionally, the suggested KNN-SMOTE-GCN model's flowchart is shown in figure 2.

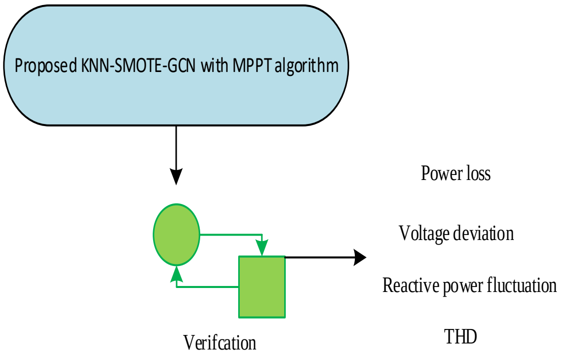

Figure 3: Typical Model Diagram for KNN-SMOTE-GCN

3.10 Graph convolutional network (GCN)

Building the association graph: A collection of nodes V and edges E may be characterized as a graph G(V, E). The connection between individual nodes v_f and v_f is signified by an edge $e_{f_g} \in E$. In order to make it easier to aggregate information in the graph framework, an adjacency matrix A is built $A[i, j] = 1$ if the edge e_{fj} exists, besides $A[i, j] = \mathbf{0}$ then.
The convolution theorem states that, in terms of forward propagation of the GCN, the Fourier transform of a convolution between two signals is the same as the pointwise multiplication of their individual Fourier transforms. Let $f * x$ Introduce the spatial domain convolution operation, which $x = \{x_1, x_2, \ldots, x_n\} \in R^n$ stands for a dataset that has n pieces of data and $f = \{f_1, f_2, \ldots, f_n\}$ are the neural network's trainable parameters. Using the Fourier transform, this procedure may be converted to the frequency domain.

$$F(f * x) = F(f) \cdot F(x) \tag{23}$$

Where the Fourier transform is denoted by F. Equation (1) may be simplified to describe the convolution process f*x in the spatial domain through the use the inverse Fourier transform F^{-1} to both sides.

$$\begin{aligned} f * x &= F^{-1}(F(f) \odot F(x)) \\ &= U\big((U^T f) \odot (U^T x)\big) \end{aligned} \tag{24}$$

Where U stands for the Fourier basis while $\odot$ means multiplication element-wise. The goal of the GCN was to provide a way for neural networks to use the association graph. The GCN does this by obtaining the Fourier basis from the graph's Laplacian matrix. What if $L_m = D - A$ is a graph's Laplacian matrix. One way to standardize it is as $L_m = I_N - D^{1/2} A D^{1/2} \in \mathbb{R}^{N \times N}$, where I_N is the neighboring matrix and denotes a unit matrix. For the degree matrix, D stands for $D_u \in \sum\ , A_{uf}$. Then, using the eigenvalue decomposition, one may derive the Fourier basis, U, and the eigenvalue matrix ∧.

$$U_\wedge U^T = L_m, \lambda = diag([\lambda_0, \ldots, \lambda_{N-1}]) \tag{25}$$

U is a set of orthogonal matrices satisfying the Fourier transform's mathematical constraints, based on the Laplacian matrix's properties. The diagonal matrix, denoted as $g_e = diag(U^T f)$. Next, we may simplify Equation (2) by following these steps:

$$f * x = U\big((U^T f) \odot (U^T x)\big) = U g_{\varrho} U^T x \tag{26}$$

Graphic convolution relies heavily on the eigenvalue decomposition of the Laplacian matrix. There is a quadratic relationship between the total amount of nodes and the computing complexity when the graph size is big. Graph convolution methods are mostly useful for small-scale networks due to the high cost of eigenvalue decomposition. Figure 3 showed in GCN model. In order to tackle this problem, Krizhevsky et al. suggested a method for approximating g_ş via Chebyshev polynomials T_k, that may be stated in the following way:

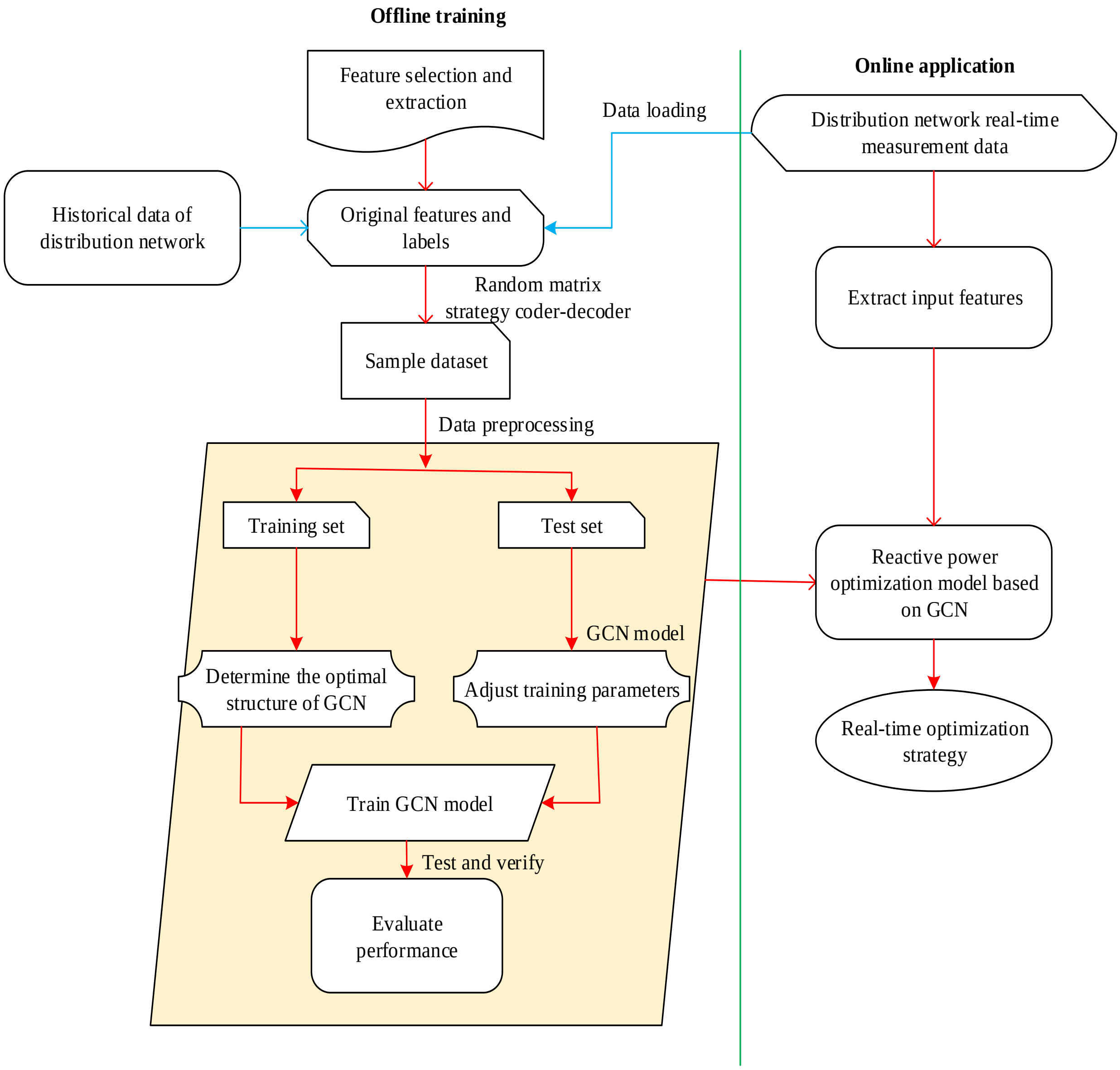

Figure 3: Proposed GCN model

$$g_\varrho(\Lambda) = \sum_{k=0}^{k-1} \theta_k T_k(\tilde{\Lambda}) \tag{27}$$

in where θ stands for the Chebyshev coefficient while T_k for the k-th element of the Chebyshev polynomial. To be more precise, it is $T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), T_o(x) = 1$, and $T_1(x) = 1.\tilde{\Lambda} = 2 \wedge / \lambda_{\max} - I_N$ contains the eigenvalues of scale in a diagonal matrix. Then, we may write (4) as:

$$f * x = Ug \circ U^T x \approx \sum_{k=0}^{k-1} \theta_k T_k(U\,\tilde{\Lambda}\,U^T)x = \sum_{k=0}^{k-1} \theta_k T_k(\tilde{L_m})x \tag{28}$$

where $\tilde{L} = 2L/\lambda_{\max} - I_N$ and $\lambda_{\max}$ stand for the highest eigenvalue of the Laplacian matrix. A more simplified version of the Chebyshev polynomials was developed by Xiao et al. $\lambda_{\max} = 0$ and $k = 2$, that is, the data is only aggregated from nodes that are in the first order neighboring the central node. This leads us to the following simplification of (6):

$$f * x \approx \theta_0 x + \theta_1 \left(\frac{2L_m}{\lambda_{max}} - I_N\right) x$$
$$\approx \theta_0 x - \theta_1 \left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}}\right) x \tag{29}$$

By setting the parameter $\theta = \theta_0 = -\theta_1$, (7) more information about:

$$f * x \approx \theta_0 \left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}\right) x \tag{30}$$

Additionally, the settings allow the network to be trained using backpropagation " W, D^c often undergo renormalization via $\tilde{W} = W + I_N$ and $\tilde{D}_{tl} = \sum_f \tilde{W}_{tl}$, that is, in turn. Lastly, the spectral domain convolution operation is defined as:

$$f * x \approx \theta\left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}\right) x = \theta\left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}}\right) x \quad (31)$$

4 Result and discussion

4.1 Configuration of PV system

This study's suggested PV system is composed of a great deal of different components. A first step involves the use of a solar panel to convert solar energy into electrical energy. Through the use of a boost converter, the output voltage of the array is thus increased while simultaneously maintaining the appropriate voltage level. A DC–AC converter is provided in order to maintain a power factor of one while converting DC to AC. In addition, a transformer is used in order to raise the output voltage to the amount that is necessary for a common connection. In order to optimize power extraction, maintain a power factor of one, and modify junction voltage, the control group of the system is comprised of a number of different strategies that have gone through extensive study. In this part, the primary issues that will be discussed are the modeling of a solar power system and the performance of the system. It begins by providing an overview of the characteristics of the PV module. It covers how the photovoltaic module reacts to variations in temperature and the amount of sunlight that it receives. Another component that is included is the boost converter, which is responsible for monitoring the reduction in the output voltage of the PV array. An exhaustive amount of information is provided on the operation of the boost converter as well as its control mechanisms, which include the MPPT approach. With the help of the MPPT technology, the photovoltaic (PV) system is able to run at its maximum power output regardless of the changing environmental conditions. A DC–AC inverter is also discussed in this section. This device converts DC energy generated by a photovoltaic array into AC power for grid integration. While discussing the operation and management of the DC–AC converter, a power factor of one is maintained throughout the discussion. Within the context of this section's treatment of the modeling, performance, and control elements of the PV system, the PV module, boost converter, MPPT method, and DC–AC inverter are all dissected in great detail.

4.2 Simulation

During this section, the performance of the system was examined at a number of different levels of direct sunlight irradiation, all while maintaining a constant temperature of 25 degrees Celsius for the photovoltaic array. Standard test conditions (STC) were used in order to determine the output of the solar panels while the temperature was set to 25 degrees Celsius. The Simulink model of the photovoltaic (PV) system, which illustrates the linked components and the interactions between them. Additionally, the mathematical model that is used to explain the solar panel's electrical characteristics is included into the PV module block, which serves as a representation of the solar panel. It takes into account the input solar radiation as well as temperature in order to generate the matching current–voltage (I–V) and power–voltage (P–V) curves. It is the responsibility of the booster converter block to monitor the drop in the output voltage of the PV array. The control algorithm that is used to guide the functioning of the boost converter via the utilization of the MPPT approach is included inside it. The Maximum Power Point Tracking (MPPT) algorithm continually analyzes and adjusts the PV system's operating point in order to achieve maximum power extraction. Through the use of the DC–AC inverter block, the DC power generated by the PV array is converted into AC energy that is compatible with the grid. Furthermore, a power factor of one is assured, in addition to the maintenance of the quality and interoperability of the AC power that is produced with the utility grid. Transformers and grid connections are two examples of extra model construction parts that might be used to depict the photographvoltaic (PV) system as a whole as well as its connection to the conventional electrical grid.

Results from a two-stage PV system with a three-level inverter and a DC/DC converter that is linked to a weak grid are shown below. Results show that the control method and inverter configuration were executed when the system was evaluated under different dynamic situations. The PV array, DC/DC converter, and three-level inverter that interface with the grid is all shown Table 1, which is the system schematic. In Table 1 we see the system's parameters. Grid voltage sag, Grid voltage swell, irradiance change, and a comparison between two-levels with three-level inverters are among the operational situations that the system is evaluated under. Voltage on the grid, current via the grid, current through the VSC, current through the PV array, and the weighted positive sequence are the critical metrics studied. The stability, power quality, as well as transient responsiveness of the system under dynamic situations may be understood by examining these factors.

Table 1: System parameters

Parameters	Value
PV Array	55
Power Rating	35 kW
Maximum Power (W)	211.802
Short-circuit current Isc (A)	9.03
Voltage at maximum power point Vmp (V)	27.9
Cells per module (Ncell)	70
Open circuit voltage Voc (V)	39.17
Shunt resistance Rsh (ohms)	312.6345
Temperature coefficient of Voc (%/deg.C)	-0.36044
Temperature coefficient of Isc (%/deg.C)	0.112
Parallel strings	7
Series-connected modules per string	23
Boost Converter	
Inductor L_{cc} (mH)	4
Capacitor $C_{ac}(\mu\ F)$	100
Voltage Source Converter	
Interfacing Inductor $L_f(mH)$	75
$RCR_f(\Omega)$	0.4
$RCC_f(\mu\ F)$	100
Grid Voltage and Frequency, (V) and (Hz)	433, 70
DC link capacitor	2200 µF
PV array current Ipv	3.46 A
Inductance L Resistor R	2 mH 0.1 Ω
PV array voltage Vdc	540 V
Grid Frequency	50 Hz
Grid Voltage rms	120 V

The experimental environment and the recommended technique's effectiveness are described in this section. Several metrics, including power loss, grid current, voltage deviation, along with grid voltage, are used to assess the system's performance via the use of the innovative KNN-SMOTE-GCN algorithm. By redistributing loads and arranging generating units, KNN-SMOTE-

GCN systems improve the efficiency of power grids. To optimize power quality, KNN-SMOTE-GCN controllers regulate the grid's reactive power, voltage, and harmonic correction. The system is constantly adjusting the control settings using fuzzy rules with real-time data to maximize power quality.

Implementation Steps

There are various essential phases involved in the implementation process. Before anything else, it is necessary to gather historical data on demand, generation, and market pricing. Additionally, forecasting models should be used in order to make predictions about future demand, renewable generation, and market prices. In the next step, the optimization problem is stated and used in order to combine the objective function, constraints, and suitable optimization solvers, such as linear programming. or mixed-integer planning. After this, the control algorithms for the first, second, and third control levels are designed and implemented inside a hierarchical manage structure. This is done in order to further govern the system. For the purpose of testing these control algorithms and verifying that they are stable and effective, the system is then simulated under a variety of market condition scenarios. With the last step, the control algorithms are implemented for real-time operation. This means that the system constantly checks and changes the distributed power resources (DPRs) based on the data that is being collected in real time.

4.2 Comparative analysis

Table 2 illustrates the existing techniques with their description.

Table 2: Comparison techniques

Technique	Description
Active Filters	To reduce harmonic distortion and enhance power quality, active filters are a useful tool.
Wavelet Neural Networks (WNN)	• These may be used in the creation of controllers for auxiliary damping.
Artificial Neural Networks (ANNs):	• Power systems may have their dynamic responsiveness improved with the help of ANNs.
Virtual Synchronous Generator (VSG)	The grid may benefit from the inertia and damping provided by VSGs.
Deep Deterministic Policy Gradient (DDPG)	• Damping controllers may be designed with the help of DDPG.

Power loss occurs in a grid system when electrical energy, in the process of transmission and distribution, dissipates as heat. Transmission or distribution losses are other names for this occurrence. A lower current density per unit of power is a common result of increasing voltage. When the voltage or current in a three-phase circuit is not balanced between the phases. Voltage or load imbalances cause an uneven distribution of electricity, which in turn causes losses. Low power factor happens when the voltage-current relationship is not ideal. Figure 4 show that when the power factor is low, the reactive power increases, leading to higher losses in the transmission and distribution systems.

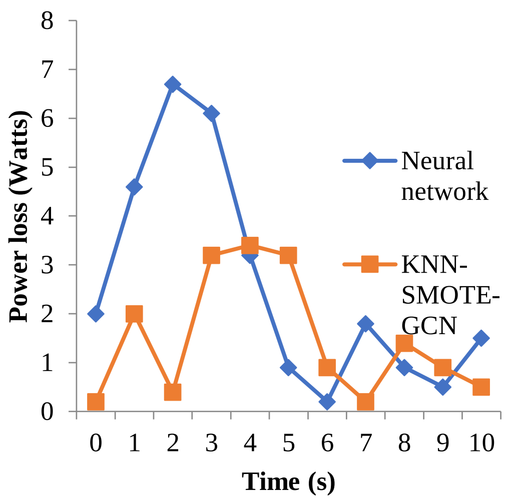

Figure 4: Power loss and time analysis

When power grid voltages deviate from their nominal or ideal values, this is known as voltage deviation. Nominal voltage standards could vary by region while kind of electrical system, although they often range from 230V to 400V and beyond. Voltage must be maintained constant and under control for grid-connected electrical gadgets and machinery to work reliably. A number of factors contribute to voltage fluctuations' potential effects on the performance and longevity of electrical devices. When the real voltage exceeds the nominal voltage, overvoltage occurs. As seen in figure 5, the term "under voltage" is used when the real voltage is less than the nominal voltage.

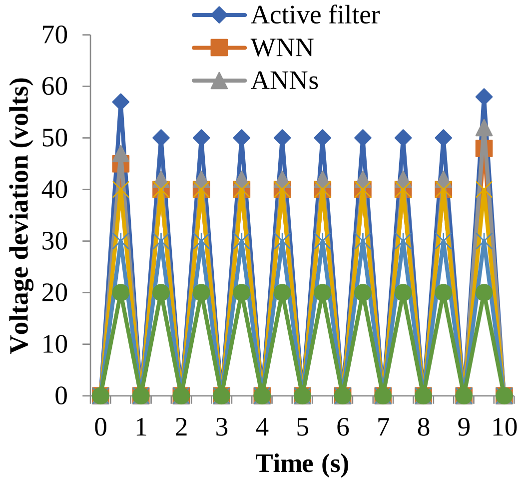

Figure 5: Voltage deviation

The efficiency, reliability, and performance of an electrical network are all impacted by fluctuations in reactive power in a grid system. Maintaining safe voltage levels and powering inductive loads both need reactive power. There are a lot of potential sources of reactive power fluctuations, which might lead to undesirable outcomes. Reactive power is a component of electrical power that does nothing useful while it sways between the generator and the consumer. "Reactive volt-amperes" is the standard measuring unit. When inductive loads are included or excluded, changes to the load profile may cause variations in reactive power. As seen in figure 6, fluctuations in generator output, especially in synchronous generators, may affect reactive power.

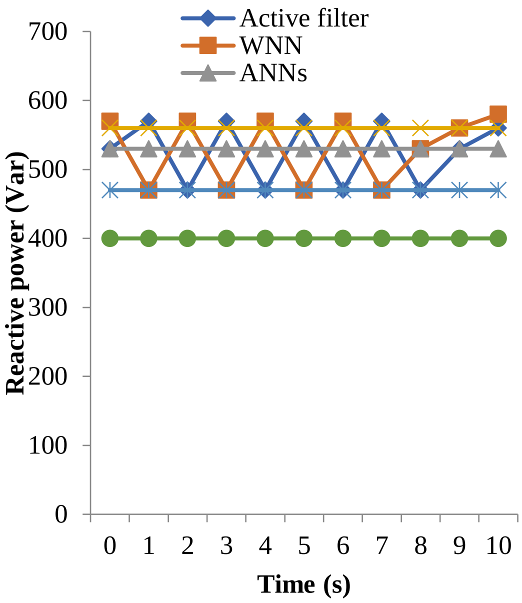

Figure 6: Reactive power fluctuation

A grid system experiences THD when harmonic components are present in the voltage or current waveform in relation to the fundamental frequency. In power systems, the fundamental frequency is typically 50 or 60 Hz, and harmonics are multiples of that. Harmonics may be caused by a variety of sources, including non-linear loads and switching operations.

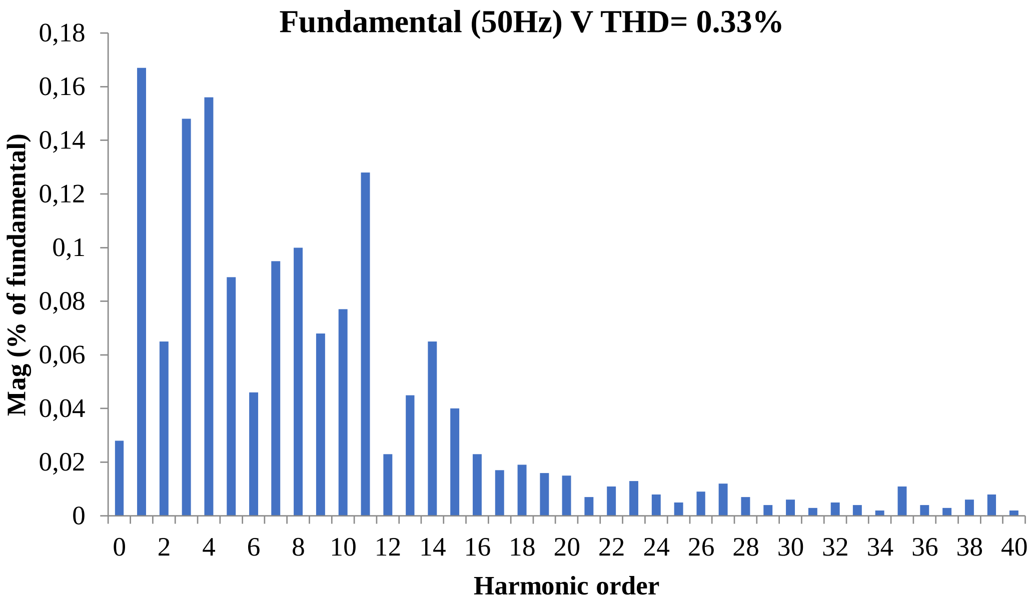

Figure 7: THD analysis

We get the THD by Figure 7 by dividing the root mean square (RMS) value of the harmonic content by the RMS value of the fundamental frequency. Typically, total harmonic distortion is expressed as a proportion of the fundamental frequency. Additionally, figure 6 shows THD in action. The performance comparison yielded better findings from the proposed work's assessment of performance. The comparative assessment has shown that the proposed model has successfully minimized the THD as much as possible. Consequently, PV systems that are linked to the grid may use it. In this study, we maximize the produced output power of the PV panel by using a DC-DC converter using MPPT. Step one involves regulating the boost converter's duty cycle. It is necessary to gradually raise the DC voltage of the PV array until it reaches a high enough voltage to meet the load's requirements. Whenever power is needed, it is transferred from the stored energy in the inductor to the load. The duty cycle, or gate pulse input, is responsible for carrying out the whole operation. It is vital to manage the duty cycle. After then, it's a matter of getting the most electricity out of the PV array in any weather. To maximize the voltage and power output of a photovoltaic array, irradiance and temperature are the two most critical elements. Therefore, it is necessary to monitor the maximum power stage, which is near the PV array's maximum power. The MPPT was created to provide a standardized, efficient tracking system. Prior research has explored a wide variety of MPPT methods for peak power tracking. Some MPPT methods, like P&O, which uses step-size control as well as oscillates around steady state in response to dynamically changing environmental variables, have been shown to have significant drawbacks, however. The incremental conductance method is more complicated and expensive [11], [19], but it responds quickly to changing conditions. The controllers utilized in this investigation yielded promising outcomes since they were based on mathematical principles. There has been an astonishing level of consistency throughout the whole energy output, leading to a steady supply of 27 MW of pumped electricity to the grid. This is true even if the amount of sunlight reaching Earth has changed during the course of the day. Many researchers and professionals in the field have taken an interest in photovoltaic (PV) systems. The incremental conductance + integral regulator strategy is one of the methods proposed for training the MPPT controller; it is referenced. The goal of developing this method was to ensure that the photovoltaic (PV) system operates at its maximum power point in all weather conditions, thereby optimizing its performance. Also, a Proportional-Integral (PI) controller was recommended as a method for controlling the DC-AC converter in the study. The conversion of direct current (DC) from solar panels to alternating current (AC) for grid integration relies on this converter. It should be noted that various control techniques become unstable when exposed to large fluctuations in solar irradiation. Keeping energy output steady is made more difficult by the fact that solar radiation is inherently unpredictable, especially when clouds are present or when the sun's beams are changing. A change in the amount of power supplied into the system could be discernible if sun irradiation decreases. Concerns about the practical applications of PV systems, particularly those connected to the electricity grid, are highlighted by this phenomenon. Although mathematically-based controllers have performed well in conditions of relatively constant solar radiation, they may require additional tuning to account for the challenges posed by sudden and unexpected changes in solar radiation. These findings are important because they show how important it is to have adaptive control systems that can adjust to new conditions and maintain a steady power supply and stable grid. Research in this area may focus on creating more resilient and flexible solar controllers in the future by combining real-time weather forecasts with sensor-based feedback systems. To further improve the reliability of grid-connected photovoltaic (PV) system [17]s, research into energy storage alternatives like batteries may also provide a means of reducing the impact of variations in sun irradiation. Solar energy consumption might be maximized with these upgrades, which would be a huge step toward creating sustainable energy and integrating systems.

A cleaner and more sustainable energy landscape may be achieved via the total performance and efficiency of photovoltaic (PV) systems, which can be enhanced through this synthesis of current approaches. Study results were very promising for the proposed system, obtained after an exhaustive series of simulations meticulously executed on the MATLAB/SIMULINK platform. The predictive control systems utilized demonstrated remarkable robustness in the face of dynamic variations in solar radiation levels, allowing for a constant energy production profile relative to the energy production profile. Additionally, the suggested system's adaptability to rapidly changing weather conditions ensures continuous and dependable energy generation, thus establishing its status as a robust and resilient energy solution alternative. As we navigate into the future of photovoltaic (PV) systems, it is wise to direct research efforts on investigating and perfecting innovative control techniques. The overarching goal is to make the system far more efficient and productive, with an unwavering commitment to producing even more remarkable and dependable results. Furthermore, the research plan includes a comprehensive comparison study, an exhaustive endeavor aimed at methodically contrasting the effectiveness of these novel control methods with the performance metrics of the current systems. The whole capability of sophisticated control techniques is expected to be exposed by using this methodical approach. By streamlining grid connectivity, these methods are poised to change the course of renewable energy generation. Ultimately, this research adds to the growing body of knowledge on renewable energy sources by introducing a new photovoltaic (PV) system and demonstrating the system's inherent capacity to address major energy and environmental issues. This contribution demonstrates the potential of state-of-the-art control systems and optimization methodologies, building a foundation for a future that is sustainable, energy-efficient, and kind to the environment.

5 Conclusion

In order to improve grid-connected PV systems, this study presented a new KNN-SMOTE-GCN method. In this case, the UPQC model is used to enhance power quality. This model controls voltage and current concerns to assure better power quality. Beyond that, the MPPT algorithm, which controls the grid system dynamically, extracts the maximum power from solar panels. By using GCN, the grid system's MMPT and UPQC operations may be coordinated to ensure optimal power quality. Hence, power loss, voltage deviation, total harmonic distortion, and reactive power variations make up the assessment criteria. In addition, we compare the resultant parameter considerations to those of more traditional models. According to the results, the created KNN-SMOTE-GCN paradigm reduced power loss by 4% compared to the other models. The voltage deviation is 26.42V and the total harmonic distortion is 0.56THD. When applied to hybrid renewable energy systems, DL models and optimization algorithms will improve BESS in the future.

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