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Improvement of Power Quality and Optimization Techniques in Power Distributed Network using Photovoltaic Inverter Control

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Abstract: Power quality is a critical aspect of any electrical distribution network, and with the increasing penetration of photovoltaic (PV) systems in power generation, ensuring optimal power quality becomes even more crucial. This abstract presents an overview of the improvement of power quality and optimization techniques in power distributed networks using photovoltaic inverter control.

The integration of PV systems into the power grid brings several challenges, including voltage fluctuations, harmonic distortions, and reactive power imbalances. These issues can degrade the power quality and affect the performance of other connected loads. Therefore, effective control strategies are necessary to mitigate these problems and enhance the power quality in distributed networks.

Keywords: PV Cell, Solar, Power Quality, Generation.

I. INTRODUCTION

As one of the greatest innovations in human history, the electrical grid is an interconnected network of generators, high voltage transmission lines, and distribution facilities for delivering electricity from producers to individual consumers. The distribution system is a part of the power system, existing between distribution substation and power consumers. The traditional distribution grids were originally built to unidirectional delivery power to cope with slowly-varying customer loads.

Due to the growing concern for the environment and the increasing load demand, more and more attention has been given to renewable energy sources. In the USA, at the end of the third quarter of 2017, there was 49.3 GW of cumulative solar electric capacity

The cost of solar photovoltaic (PV) is already competitive with fossil fuels in some markets around the world. As the solar PV industry scales, the price is expected to further decline in coming decades. The increasing penetration of distributed PV generation presents both challenges and opportunities for distribution networks [2].

Due to the cloud movement, the solar power is highly intermittent and hard to predict. Figure 1.1 shows plots of solar irradiance data for two typical clear and cloudy days. This kind of rapidly varying irradiance conditions introduces several challenges. For example, PV generation can cause node voltage rise.

Although the intermittent nature of the PV generation poses a number of significant challenges at the distribution level, at the same time, the PV generation units can actually contribute to the improvement of the power quality and also serve to save energy. If combined with appropriate Volt/Var control algorithms, the PV DC-AC inverters can address the challenges in high penetration of renewable resources. The DC-AC inverters are power electronic devices that are used to couple DC to the AC grid. The primary function of the inverter is to deliver the DC power to the AC side as efficiently as possible. At the same time, many inverters already deployed today can provide a new reactive power management by injecting or absorbing reactive power into or from the grid, respectively. When the capacity of the PV inverter is not fully used by the real power delivery, it can work as Var regulation device [5]. The reactive power of PV inverters can be changed continuously with extremely fast speed (in milliseconds). A large number of recent studies [6]-[81 in the literature have explored the possibility of utilizing PV inverters to improve the power quality of distribution systems with high renewable penetration levels. As the share of the intermittent sources increase in the future, PV inverters are likely to take over the grid tasks together with the conventional control devices, such as OLTCs and SCs.

The location and size of PV inverters play a vital role in voltage quality and power losses of distribution systems. The traditional Deterministic Load Flow (DLF) analysis, which uses specific values of power generation and load demand, is unable to capture the variations and uncertainties of the PV output and load demand.

The results calculated from DLF may be unrealistic. Contrast to the DLF, the Probabilistic Load Flow (PLF) is first proposed in 1974 [91 and has been applied in power system short-term and long-term planning as well as other areas [10]. The inputs of the PLF are formulated with Probabilistic Density Function (PDF) or Cumulative Distribution Function (CDF) to calculate system states. The outputs of PLF are in terms of PDF or CDF to include and reflect the uncertainties of the system. In this dissertation, the PLF method is used to assess the optimal location and capacity of the PV generation units.

II. LITRATURE REVIEW

It should be noted that the literature papers deals with the Distributed Generations (DGs) placement problem in two different ways: analytical and numerical. In [14], an analytical approach to place distributed generation (DG) to minimize the power loss of the system is presented. Because the load flow equations are non-linear, they must be linearized in order to make the convolution solvable. The common linearization methods are based on Gram-Charlier expansion and CornishFisher expansion. Due to the approximation process, the analytical method, while quite mathematically elegant, may not be suitable to perform on a complicated system with large nonlinearities.

The numerical method performs a large number of DLFs with inputs determined from the samplings of the random variables in the PLF. The most common numerical method is the Monte Carlo method. A Monte Carlo based method for optimum allocation of PV generation is presented in [15] to minimize the power loss. Given the time-varying nature of the load and the intermittent nature of solar energy, the Monte Carlo method is a good approach when uncertainties are involved in the optimal allocation of PV generation problems. In the Monte Carlo Simulation (MCS) method, every sample value is accurate without any approximation. The accuracy and convergence of MCS are guaranteed by the probabilistic limit theory. In some papers, the distributions of the PV generation output and load values are assumed to have a predefined probability density function, such as the uniform distribution in [151, the Gaussian distribution in [161, or the Weibull distribution in [17], which are difficult to perform on a realistic system. OPF problem seeks to optimize a certain objective function, such as voltage fluctuation, power loss, and/or utility elements cost, subject to power balance, Kirchhoff's law, as well as capacity, stability and operation constraints on the voltage and power flows.

There has been a great deal of research on OPF since first formulated by Carpentier in 1962 [l I l. OPF problem is generally nonlinear, nonconvex, and NP-hard. A large number of relaxations and optimization algorithms have been proposed to solve this problem [18].

A popular approximation of OPF is the DC power flow problem. The OPF problem is linearized and therefore easy to solve [19], [20]. Nevertheless, this method is not adequate enough to solve the OPF problem with non-smooth objective functions. In [21], a coordination strategy to minimize the total number of tap changer operations is proposed. The interior point method is applied to solve this optimization problem. However, the interior point method is not suitable to solve the non-convex problems due to the global optimum cannot be guaranteed.

Instead of solving the OPF problem directly, the authors in [221 propose a method to solve the convex Lagrangian dual problem of the original OPF problem. This provide a way to determine for sure if a power flow solution is globally optimal for the nonconvex problem. The authors in [23] present a systematic approach to determine the active and reactive power set points for PV inverters. The sparsity promoting regularization and semidefinite relaxation techniques are applied to reformulate the original OPF problem. The limitation of semidefinite relaxation for OPF is presented in [24]. It is proved that the sufficient condition of [22] always holds for radial networks.

However, as a line flow constraint is tightened, the sufficient condition fails to hold for some mesh networks. Hence it is important to develop systematic methods for solving OPF involving radial networks and mesh networks. In [25], the backtracking search optimizer algorithm is applied to solve the reactive power dispatch problem, but only a single time-point is considered in the optimization problem.

III. METHODOLOGY AND DATA ANALYSIS

The procedure of identifying the optimal location of a PV plant is depicted in Figure. Identifying the optimal location of PV plant is considered as a system planning task which requires high accuracy, so we use full enumeration to ensure the global optimal result. Every possible location is tested in this simulation. The process of identifying the optimal PV location is repeated until the constraints on the bus voltages are satisfied.

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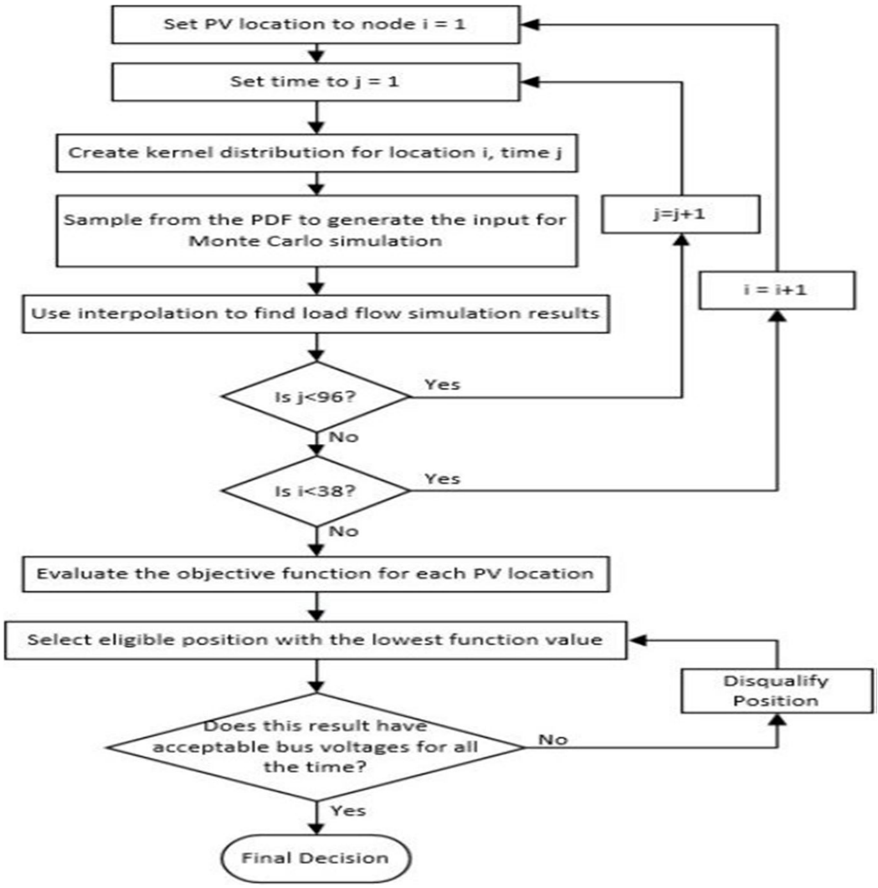

Figure: The flowchart of the proposed algorithm to determine the optimal location of the PV plant.

Kernel density estimation is closely related to histogram, but has more favorable properties when given suitable kernel function and bandwidth. To see the difference, Figure 2.2 shows the histogram plot and kernel density estimation plot of one-year PV plant output at I pm. The advantages of KDE include that the estimated probabilistic density function is smooth and continuous; the relationship between adjacent data is considered; and it is a nonparametric density estimation procedure

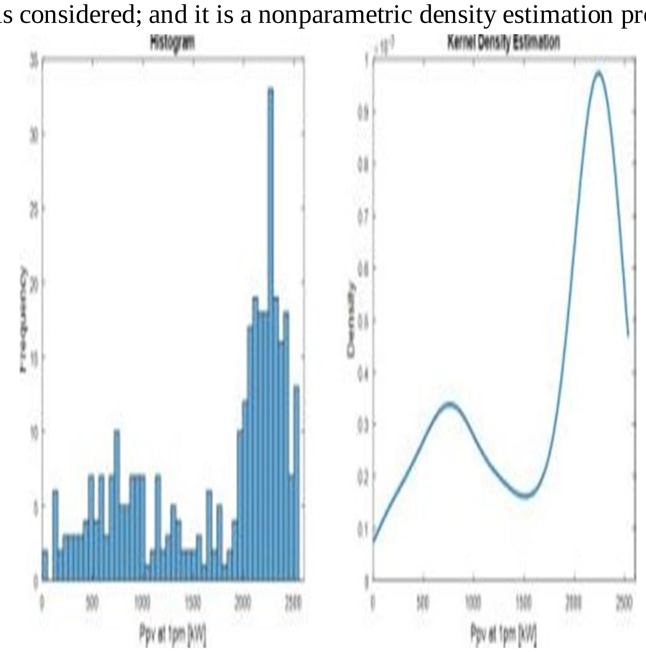

Figure: Comparison of the histogram and kernel density estimation methods using the same data set.

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IV. ISSUES WITH RECOMMENDATIONS

For the first stage, the total time window and time interval are initialized. The maximum sample size of the multi-start approach is set. In the next stage, according to the nature of the design variables (continuous or discrete), either the PSA or the GA are selected to solve the optimization problem. In the iteration process, the objective function is evaluated by calculating the load flow. This process is treated as a black box, and can be applied either on radial power grids or on complex mesh networks. When the stopping criteria reached, the optimization process is finished. At last, the global optimality is identified among the local minima. A brief description of multi-start structure and the two algorithms is given in the following subsections.

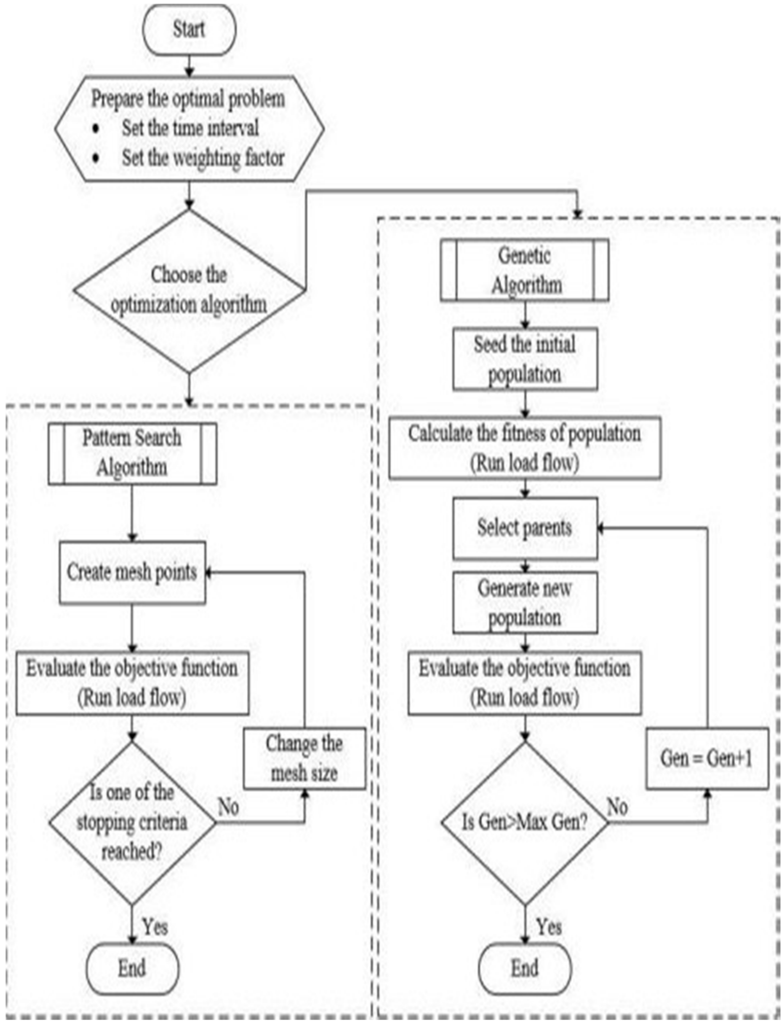

Figure: Flow chart for main stages of the day-ahead optimal scheduling.

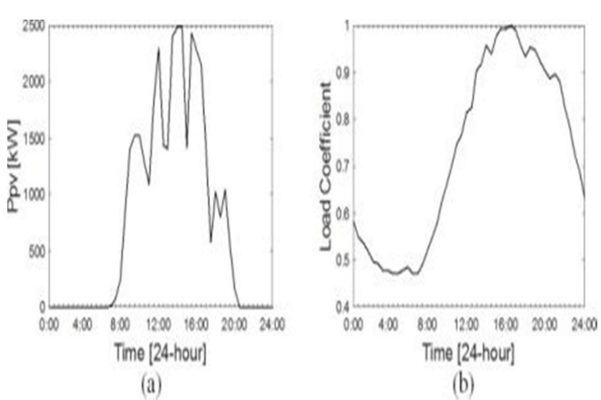

Figure: Forecasting results: (a) Real power output of the PV plant; (b) Normalized load profile.

In the real-time optimization problem, the only decision variable is the reactive power of the PV inverter with the constraint of the PV inverter capacity. The objective function and other basic constraints are similar to those in the dayahead optimization problem, and so are not repeated here.

To solve this nonlinear optimization problem, the pattern search algorithm is applied. The algorithm directly searches the optimal value of QPV so that the objective function is minimized. During each iteration, the objective function is evaluated via power flow calculation. The inputs of the power flow calculation are the active power and reactive power demands at each bus.

The Opal-RT workstation is a PC that has RT-LAB installed. RT-LAB is a real- time simulation software fully integrated with MATLAB/Simulink. The distribution system model is first developed in MATLAB/Simulink environment, and then the model is compiled and loaded to the Opal-RT simulator. With the State Space Nodal (SSN) solver [74] and parallel computation, the Opal-RT simulator can provide an effective way to simulate large and complicated system in real time. The measurements of the power system are sent from the Opal-RT simulator to the local controllers as analog output signals.

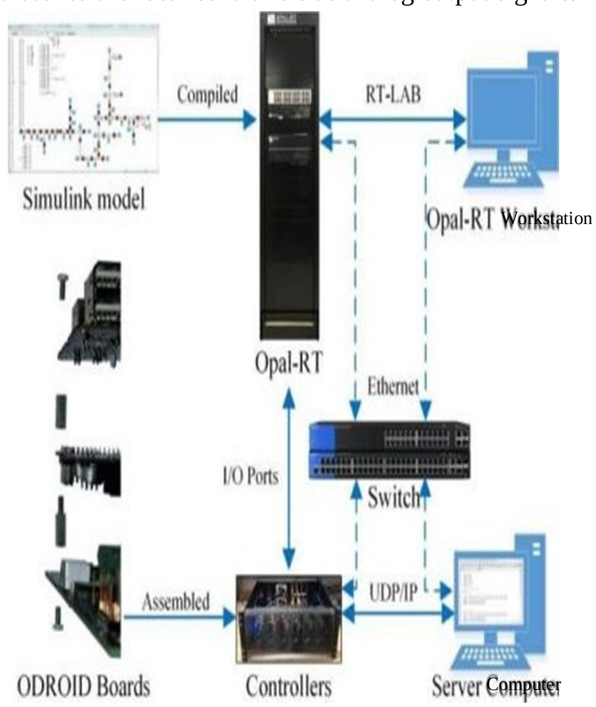

Figure: Structure diagram of the real-time HIL simulation platform.

The controller, also referred to as the ODROID board in this paper, consists of three layers, and the details of these different layers are listed. Due to the low cost and powerful computing ability, the first layer is the ODROIDU3+ computer. The key function of this computer is UDP/IP communication implemented in C++. The ODROID board is interfaced with the OP5607 simulator through standard I/O ports. Hence, the second layer is designed to offer expansion I/O ports. The third layer is designed to ensure the analog signals are within a specified safe voltage range. In this paper, the ODROID boards are designed as local controllers, but can also be used as measurement devices to send measurements of the power system to the server computer. The server computer is a Linux PC with telecommunication and computation capabilities.

The software implementation is illustrated in Figure 4.3. First, the day-ahead optimal scheduling is applied to the system. The ODROID boards receive the measurements from the OPAL-RT simulator via I/O ports, and then send the measurements to the server computer. The communication between the ODROID boards and the server computer is realized through UDP/IP protocol. Each control board is assumed to be installed at the bus with a critical component of the distribution system. To run the optimization algorithm, the load demand of every bus must be used as the input for the Newton-Raphson load flow calculation. As described in previous section, the ANN approach is applied to estimate the remaining states of the system. The reactive power of the PV inverter is then calculated via the pattern search algorithm and broadcasted to all the ODROID boards. The control board installed at the PV generator bus sends the optimization result, i.e., the optimal reactive power of the PV inverter, to the OPAL-RT simulator. Finally, the reactive power of the PV inverter is updated according to the received control signals.

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To synchronize the measurements sent from the ODROID boards to the server, the ODROID boards will wait for the control signal to be sent back to trigger the next loop. The process is repeated to minimize the total voltage deviations and power losses of the distribution system.

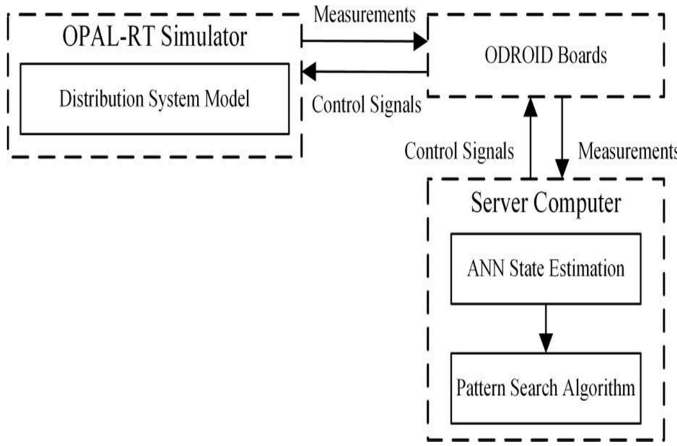

Figure: The flow chart of the communication and software implementation.

To evaluate the performance of the proposed optimization approach, a modified IEEE 34-node test feeder is tested, as shown in Figure. The system parameters, as well as the peak values of active and reactive loads are adopted from [64]. The modified IEEE 34-node test feeder consists of a PV generation unit and various types of loads. In this distribution system, there are two OLTCs and two SCs. A PV plant is connected at node 840 (renumbered as node 34 in our case) with the capacity of 1.5 MVA. The tap changer is set with ±10 taps with 1% voltage regulation per tap. There are six local controllers installed at the substation, OLTC1, OLTC2, SC1, SC2, and PV inverter node.

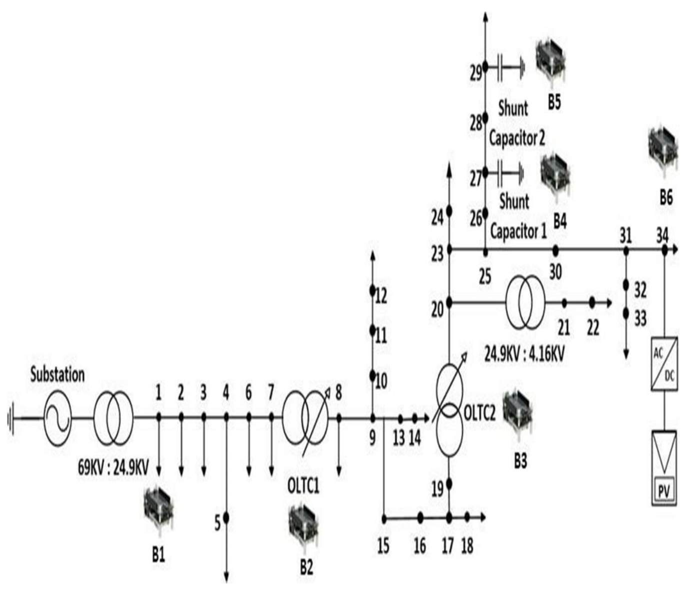

Figure: Single-line diagram of modified IEEE 34-node test feeder with 6 controllers installed.

In this work, the centralized ANN state estimation method is used. The active and reactive load profiles over one year are provided at every half-hour interval, and white noise is added to the domestic load, commercial load, industrial load and street light load, at levels of 15%, 15%, 10%, and 5%, respectively. The inputs and outputs of the proposed ANN approach are summarized in Table 4.2. Real measurements are assumed to be mainly available at the node with critical components (where the ODROID boards are installed). There are 16 real measurements chosen to be the ANN inputs, including the real power and reactive power generated from the substation, power injected into the nodes and the node voltage magnitudes. The ANN outputs are the load demands of each node (there are 6 nodes without loads, i.e., nodes 1, 6, 7, 8, 19, and 21).

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Table 4.2: Summary of ANN Input and Output

Node	Controller	ANN Input	ANN Output
1	B1	P_g, Q_g	P_{L-2}, Q_{L-2}…, P_{L-5}, Q_{L-5}, P_{L-9}, Q_{L-9}…, P_{L-18}, Q_{L-18}, P_{L-20}, Q_{L-20}, P_{L-22}, Q_{L-22}…, P_{L-34}, Q_{L-34}
8	B2	P_{inj-8}, Q_{inj-8}, V_8	
20	B3	P_{inj-20}, Q_{inj-20}, $V20$	
27	B4	P_{inj-27}, Q_{inj-27}	
29	B5	P_{inj-29}, Q_{inj-29}, $V29$	
34	B6	P_{inj-34}, Q_{inj-34}, P_{PV-34}	

Simulation Results

Day-ahead optimal scheduling results For the day-ahead optimal scheduling problem, the optimal setting values of the OLTCs, SCs, and PV inverter are calculated based on the forecasted values of PV output and load demand. The comparisons of the forecasted results and real measurements are illustrated in Figure 4.5. The optimization process is applied on a 24-hour time scale with a resolution of 30 minutes. The PV output is mainly governed by irradiation. There is notable forecast error due to the fast cloud movement. Compared to the uncertainty of the PV output, the load power demand follows a more predictable pattern.

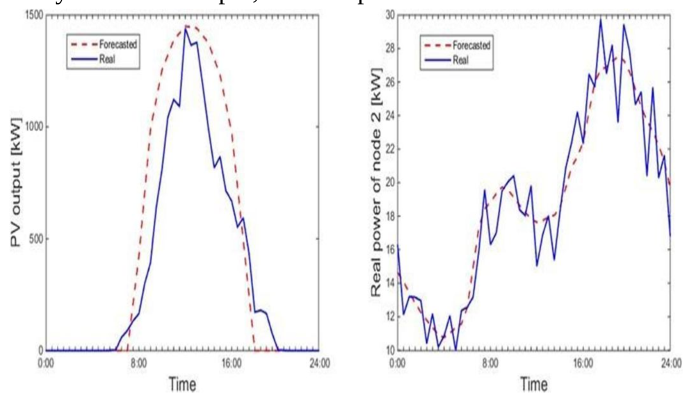

Figure: Comparison of the forecasted and real values of the PV output and the real power injected to the node 2.

Monte Carlo sampling, based on the kernel distributions described in the previous step, is used to create input parameters for the simulation. First, the kernel distribution is converted to a PDF with a fineness of 1,000, meaning that the relative probability is calculated at 1,000 points along the range of possible values for the variable in question. This PDF is then passed through a cumulative sum operation and normalized, so that a vector is generated with length 1,000, beginning at 0 and ending at 1. 10,000 random numbers between 0 and 1 are generated, and interpolation method is used on the cumulative sum vector to determine the corresponding variable value. Thus, random numbers will fall on the variable values with the highest probability density most often, since the cumulative sum will increase the most for the variable values with the highest probability density. Figure 2.3 shows the results of the Monte Carlo sampling of the kernel distribution shown in the right graph in Figure 2.4. corresponding to three different variables randomized by the Monte Carlo method: PV real power generation, load real power consumption, and load reactive power consumption. Each simulation uses one input parameter from each of the three sets; that is, the i^{th} simulation of 10,000 would use the i^{th} entry from each of the three lists.

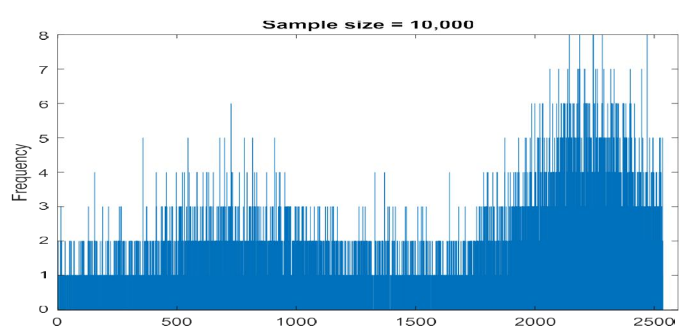

Figure: Sample results of PV output for Monte Carlo simulation.

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A problem arises when attempting to run the many simulations that the Monte Carlo method requires. Even with all possible optimizations, such as combining cases at nighttime when the output of the PV plant stays zero, and simulating the load flow in parallel on a 12-core machine, running all the necessary simulations would still take over a month. This problem is circumvented by establishing reference values for the result parameters (power losses, voltage deviation) at different values for the input parameters (PV location, PV power generation, load real power consumption, and load reactive power consumption). Then, rather than running a different simulation for each Monte Carlo input parameter set, interpolation is used to determine the corresponding output values from the 5-dimension input set. Because of the smooth change in output values with a change in input values, and the high number of similar input parameters that comes with Monte Carlo simulations, interpolation proved to be a highly effective way to reduce computational overhead. Fig.6 shows a wireframe mesh of the voltage deviation for the circuit as load real power and PV real power are changed, while PV position (bus 38) and load reactive power (0 Var) are held constant to allow the results to be visualized in three dimensions. The range of PV and load real power covers the full collection of values possible for the case study used: 0 to 2.6 MW for PV real power and 1.4 to 7.5 MW for load real power. The x- and y-axis values denote the fineness of the reference grid; 25 different evenly spaced load values are sampled along with 20 different PV generation values.

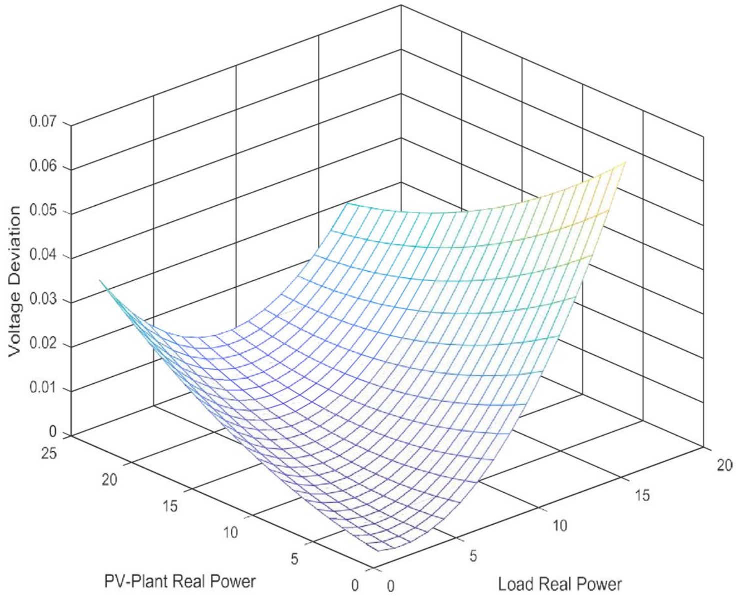

Figure: Sample of interpolation reference values.

V. CONCLUSION

The integration of photovoltaic (PV) systems into power distributed networks presents both opportunities and challenges. While PV systems offer clean and renewable energy generation, their integration can introduce power quality issues such as voltage fluctuations, reactive power imbalances, and harmonic distortions. This research focused on the improvement of power quality and optimization techniques by employing effective control strategies for PV inverters.

Through the implementation of various optimization techniques, significant advancements have been achieved in power quality parameters. The use of maximum power point tracking (MPPT) algorithms ensures optimal power extraction from PV panels, maximizing energy generation and improving system efficiency. Voltage regulation techniques maintain a stable output voltage from the PV inverter, mitigating voltage fluctuations and ensuring a steady power supply.

Reactive power control plays a crucial role in balancing the reactive power flow between the PV system and the grid. By dynamically adjusting reactive power injection, the power factor can be optimized, leading to efficient power transmission and reduced losses. Harmonic mitigation techniques effectively suppress harmonics generated by the PV inverters, minimizing distortion in voltage and current waveforms.

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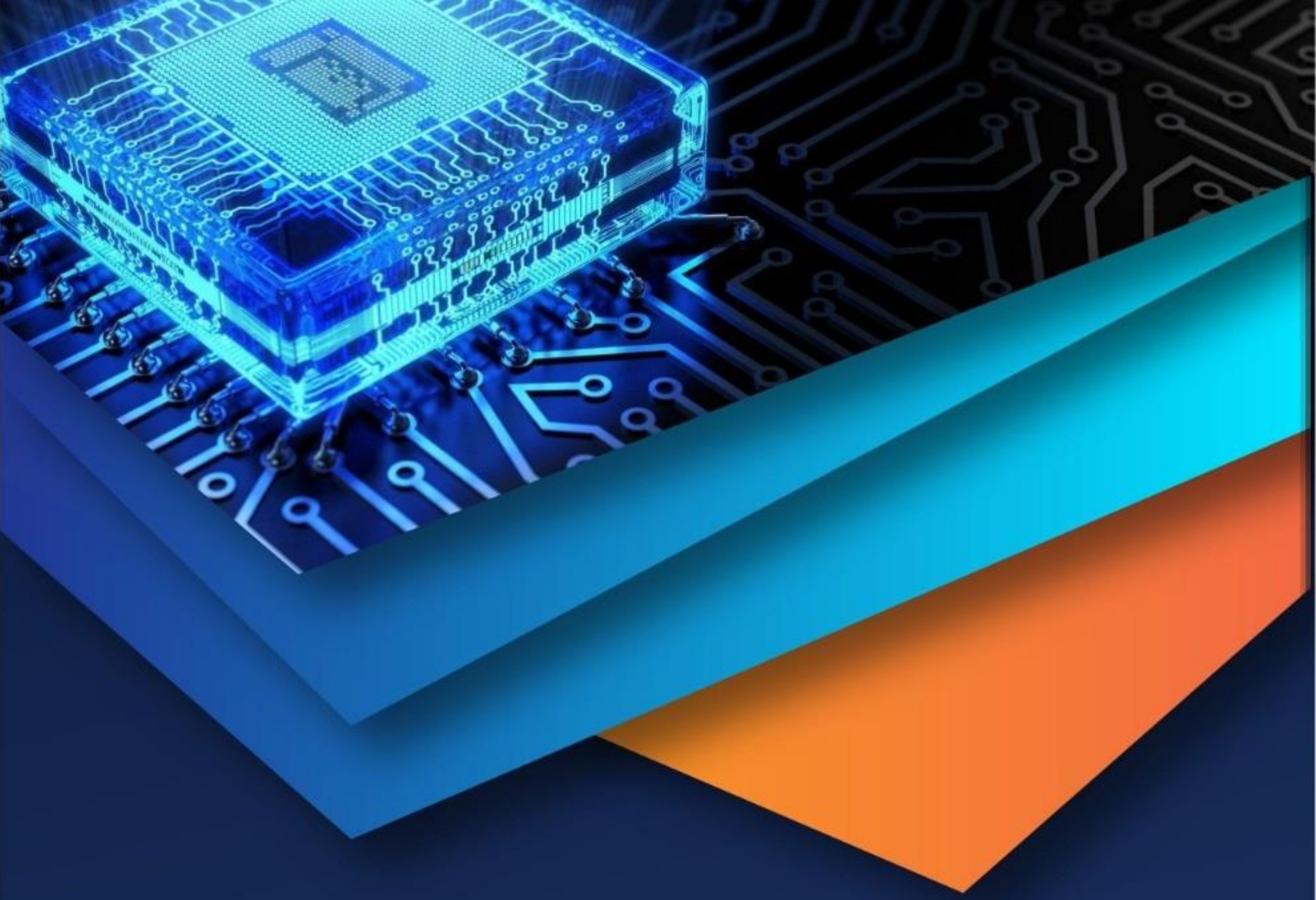

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