J. Electrical Systems 20-10s (2024):4147-4160

Yan Huan[1], YUE Yuan-Yuan[1], JIA Hong-gang[1], HUI Zijia[1], ZENG Hao[*2]

Spatio-Temporal Analysis and Modeling of Distributed Photovoltaic Contributions to Distribution Network Safety

Journal of Electrical Systems

Abstract: - Study presents a computational technique to explain how various types of loads in a distribution system affect the PV (photovoltaic) systems. This strategy will depend on the type of relationships between PV generation and load demand across time and space to improve the stability as well as safety of the distribution system. Initially, this paper includes mathematical modeling of PV systems with loads. Then, we use a dataset that comprises PV data, environmental data, and network data. Furthermore, PV configuration and distribution systems are depicted in depth using Geographic Information System (GIS) technology, giving a visual depiction of their placement about load regions and network architecture. To understand the effects of temporal shifts in PV output on network safety and stability, we used neural networks (NNs) to assess temporal patterns, combining PV along with load demand data. To simulate this study, we use the MATLAB platform regarding various features of data assessment. Moreover, load flow analysis (LFA) is carried out to assess how PV generation affects the voltage, power, etc. Simulations at various fault conditions are also conducted in this paper. Dynamic stability assessment integrates both temporal and spatial information for complete comprehension, identifies probable risks and stability boundaries, and evaluates network response to disturbances using dynamic modeling using the MATLAB platform.The examination explores the impact of PV insertion, evaluates the geographical spread of PV networks, and identifies potential risks and barriers. It also studies the distribution system's present status absent PV additions.

Keywords: *Photovoltaic (PV), distributed system, safety, stability, spatio-temporal, neural network (NN)*

1. INTRODUCTION

Photovoltaics or PV is a process of producing electricity by converting solar light into direct current electricity with the help of electrodes, which are made of semiconductor materials that show photovoltaic impact. The photovoltaic impact is a physical and chemical process of generating an electric current in a substance when exposed to light or in this case light from the sun [1]. PV methodology mainly combines the utilization of solar panels that consist of several solar cells manufactured from semiconductor materials, mainly silicon. These solar cells can absorb sunlight and this in turn frees up electrons embedded in the semiconductor material, producing electron-hole pairs. The free electrons that are produced are collected and directed to flow, forming an electric current that can be used for power [2].

The major forms of PV technologies are mono-crystalline silicon, polycrystalline silicon, thin films, and advanced technologies that include perovskite solar cells. They all have their own strengths and weak points concerning their cost and speed and their areas of usability [3]. Photovoltaic systems can be installed singly in residential homes on the roofs to large photovoltaic power stations that feed straight into the power grid [4]. They can also be incorporated into structures (BIPV or building integrated photovoltaic), or used individually, for example, in operating distant tools. The advantages of using PV systems include that PV systems offer clean energy to the users without affecting the environment. They eliminate dependency on fossil fuels,cut the emission of greenhouse gases, and

[1]State Grid Shaanxi Electric Power Company Limited Research Institute, shanxixian,710065, China
[2]WLSL ELectric Energy Star,Inc Electric Energy Star Co.,Ltd(Chongqing) ,Chongqing， China. 400039
Corresponding Author,
ZENG Hao
E-mail: 13648334204@163.com

provide a renewable way to satisfy the world's increasing energy needs [5]. Furthermore, there are constant technological enhancements in the efficiency of the PV systems, lessening the costs of solar energy and its comprehensiveness.

The PV contributions to the safety of distribution networks include the connection of the photovoltaic systems to the network of electricity and the protection of the distribution network as well as power distribution safety [6]. In the case of PV networks dispersed in a network fashion, they offer some safety advantages but at the same time present difficulties that have to be addressed. PV systems enhance the safety of distribution networks in the sense that they offer distributed power production with less load on conventional power plants and subsequent distribution networks [7]. This decentralization could enhance the grid in conditions of extra demand or failure of central power plants. In addition, for more complexity, PVS can contribute to voltage support and power quality since it can provide reactive power.

Nevertheless, the fluctuating characteristic of solar energy proves disadvantageous for the stability of the grid [8]. These variations result in fluctuations of power supply that should ideally be avoided for stability reasons thatfindings from weather changes. Such undesirable consequences can be addressed by sophisticated prognosis and energy storage systems because of their ability to manage relations between demand and supply. Expenses are also kept under check through ways like having smart inverters and grid-forming inverters that assist in controlling voltage and frequency [9]. Besides, well-executed grid management measures like monitoring and control of the grid can prevent PV integration's negative impact on the network's safety. Consequently, distribution network safety benefits greatly from the incorporation of PV systems, although the design for system integration entails proper management and technology solutions considering the fluctuation of energy production as a challenge to power stability [10].

This paper aims to develop a computing strategy to assess how different loads impact photovoltaic systems, enhancing distribution network stability and safety through mathematical modeling, spatial-temporal analysis, and dynamic stability analysis.

Contribution

- Network planning is aided by the spatial analysis that shows a moderate clustering of PV systems with high-density areas detected by DBSCAN.
- Peak PV generation is shown by temporal analysis that it occurs between time intervals with significant seasonal changes, emphasizing the necessity of adaptive energy management.
- Improved fault detection is necessary because increased PV penetration lowers voltage and decreases stability. Transformer failures have a greater influence on network reliability than feeder line damage.

2. RELATED WORK

The PV Project of Million Household Rooftop was the main subject of Yu and Tong[11], which investigated the locational method for recycling eventually-used solar modules. Under extended producer responsibility, it contrasted two recycling scenarios that are producer cooperative recycling and municipal recycling. Efficient recycling programs for end-of-life PV modules should be encouraged by using the extended producer liability principle.

A general structure was created by Guo and Kluse [12] to maximize the financial effectiveness of recycling photovoltaics. From the standpoints of capital costs, operating costs, and transportation costs, the total recycling cost was optimized. A mathematical methodology was produced to pinpoint the exact locations of facilities for solar energy recycling to carry out the optimization.

According to Oteng et al., [13], their model, which makes use of the Weibull distribution,would produce enormous amounts of PV waste. More than 20% of homes have already installed small-scale solar photovoltaic (PV) systems, marking a major shift in the electrical market. As a result, there was an increase in PV waste that affected the sustainability of the environment. A comprehensive reverse logistic network might save expenses and have less adverse environmental effects, according to the research.

An extensive structure for environmentally friendly neighborhood-scale power plants combined waste-to-energy and rooftop photovoltaic technology was presented in Ji et al., [14]. It compared financial, effectiveness, and environmental sustainability, optimized design, and evaluated local renewable energy sources. The findings demonstrated that although grid-connected hybrid structures had significant carbon emissions, they rather rely on conventional energy sources.

To enhance customer baseline load (CBL) calculation for incentive-based demand-side reaction initiatives, Li et al., [15] suggested a PV-load decoupling paradigm. The structure required historical PV output power statistics to isolate PV output power from real load power. For small-scale distributed photovoltaic systems (DPVS), subsequently, their data was typically absent.

A decoupled two-stage estimate method was presented by Li et al., [16] for reliable estimation of the aggregated baseline load (ABL) in behind-the-meter photovoltaic (BTM-PV) plants. The first stage had customer load and PV power separated from the net load using a limited set of accessible smart meter data and PV power. The stageof second uses a weather classification-based solar electricity estimating method to estimate customer load and PV power individually.

Significant environmental benefits were found by Deng et al., [17], who examined the life-cycle of solar power plants. According to the study, centralized photovoltaic power plants can cut carbon dioxide emissions by enormous amounts, with a 1.89-year carbon recycling period. Theymight encourage the minimization of climate change and boost the use of photovoltaic energy.

Transmission over long distances of electricity in large-scale PV power plants was investigated by Yang et al., [18]. Maximizing the financial benefit of PV power storage and energy storage was the goal. A lithium battery effectiveness concept was used in the investigation. Reducing the amount of electricity that was abandoned annually, the ideal storage capacity for energy, and a two-year replacement period were the optimum.

Anautomatic machine learning-based waste recycling framework (AMLWRF) for autonomous material classification and separation in mixed recycling applications was proposed by Chen, [19]. The study proposed to use IoT and image analysis for intelligent trash management while examining machine learning techniques in systemsfor recycling. These gadgets can increase efficiency and offer real-time data on waste-generating activity.

An energy management model was presented by Gao et al., [20] that considers the lifecycle of lithium batteries, installation specifications, data on electricity usage, and data on photovoltaic power generation from a manufacturing facility. Lithium batteries in particular were essential for energy storage to eradicate volatility. However, power consumption limits capacity size, which makes scheduling challenging. The appropriate storage capacity and running expenses were minimized by the framework.

By using the Internet of Things (IoT) to provide real-time garbage collection system monitoring, Al Duhayyim et al., [21] attempted to solve the global dilemma of rising waste output as a result of industrialization and urbanization. Utilizing IoT-based sensors of the camera, a microcontroller for processing data, and a residual network approach-based feature extraction system for trash classification, the method of deep learning wasan optimized artificial environment using improved deep learning techniques.

An efficient solar PV generation forecast model was created by Kim et al., [22] to help solar power plants create stable supply-and-demand power grid networks. By applying the machine learning approach with the stacking ensemble method, a multisite hybrid spatio-temporal framework with exceptional performance was produced. By including knowledge that the previous single-site model did not acquire, the upgraded system improved its ability to address climate change.

Toinvestigate solar photovoltaic (PV) adoption patterns in spatiotemporal patterns, Peralta et al., [23] used artificial neural networks (ANN) as the decision-making criterion, taking social dynamics and temporal and spatial relationships. The model generated information from past PV data and adjusted to trends by utilizing the approximation capabilities of ANN. After developing an autoregressive model, socioeconomic factors were included to better account for population variability.

To advance power production technology, a deep learning neural network framework for spatiotemporal PV prediction was presented in Dai et al., [24]. A single long short-term memory (LSTM) or convolutional neural network (CNN) algorithm trained on the same dataset was used to compare the approach against. Strong spatiotemporal correlation between sites was considered by the CNN-LSTM model that performed admirably on assessment indices metrics, leading to improved prediction accuracy.

3. METHODOLOGY

The methodology includes mathematical modeling of PV systems and loads. The dataset used in this study comprised PV data, network data, and environmental data, each containing 1,000 instances. PV configurations are visualized using GIS technologies. Temporal patterns are analyzed using neural networks. MATLAB is used to model dynamic stability and load flow analysis in a variety of failure scenarios.

3.1. PV mathematical modeling

Numerous solar cells linked in parallel or series form a PV module. Creating an analogous circuit with the 5-parameter concept as its basis is made up of a parallel resistance, a diode, a current source(R_{pc}), and a series resistance(R_{sc}), is a popular method for modeling solar cells. Equation (1) can be used to illustrate the mathematical model of the one-diode PV, and Figure 1 depicts the analogous circuit.

$$I = I_{ph} - I_d - I_P = I_{ph} - I_0[\exp\left(\frac{V+I.R_{sc}}{V_t}\right) - 1] - \frac{V+R_{sc}I}{R_{pc}} \tag{1}$$

Where $V_s = n.K.\frac{T_d}{q}$is voltage of thermal (V) of the diode, $n$is the perfection characteristic of diodes, $q$is the electron charge ($1.602E - 19C$), $K$is the constant Boltzmann's ($1.381E - 23\,J/K$), and T_d is the solar cell temperature in kelvin (K). WhereI_{ph} is the current (A)created by light, I_0 is the diode's reserve saturation current (A), R_{sc} is the solar cell's series resistance (Ω), R_{pc} is the solar cell's parallel resistance (Ω), and $T_d$is the solar cell temperature (K).

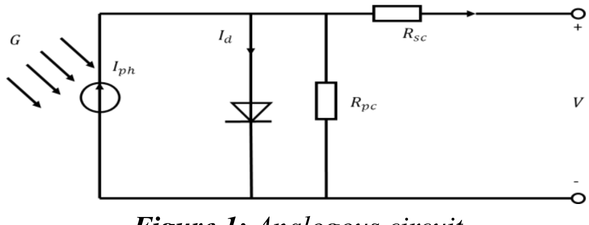

Figure 1: *Analogous circuit*

When a PV module consists of many solar cells linked in series. The module's output voltage V and output current $J$are related by Equation (2).

$$I = I_{ph} - I_0\left[\exp\left(\frac{1}{V_t}\left(\frac{V}{N_s} + I.R_{sc}\right)\right) - 1\right] - \frac{1}{R_{pc}}\left(\frac{V}{N_s} + R_{sc}I\right)$$
$$= I_{ph} - I_0\left[\exp\left(\frac{V+I.R_s}{N_sV_t}\right) - 1\right] - \frac{V+R_sI}{R_p} \tag{2}$$

Here$N_s$are the several cells in series within a module, $R_s = N_s.R_{sc}$is the resistance of a module in series (Ω), and $R_p = N_s.R_{pc}$is the parallel resistance of a module (Ω).

3.2. Spatio-temporal analysis

Spatial-temporal analysis of photovoltaic (PV) systems combines spatial and temporal methods to understand distribution patterns and forecast performance. This approach enhances network safety by optimizing energy management, addressing distribution patterns, and ensuring reliability through precise forecasting and clustering insights.

3.2.1. Spatial analysis

In this spatial analysis of photovoltaic (PV) networks, various methods are included and firstly, GIS technology was employed to improve distribution system safety through a comprehensive understanding of PV system distribution patterns.

Spatial Autocorrelation: Using the GIS technique, this study estimated the spatial decision-making by using Moran's I and Geary's C, whereby Moran's I was used to establish the general tendency of the PV systems to cluster in some specific region while Geary's C examined the tendency of the PV system to cluster in a specific region. These are valuable conclusions if performed using GIS mapping and necessary for the identification of regional hotspots of PV systems to achieve the proper distribution network load management and avoid risks of energy overloads.

Clustering Analysis: The application involved the use of GIS and the clustering method. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was used to extract the locations of clusters and the spotlight of PV systems. Concentric circles radiating outward from the center present high-density clusters visible via GIS mapping, while other sections labeled 'noise' illustrate low density. Such patterns involve the analysis of geographical patterns to plan and improve infrastructures that GIS technology aids in. By attending various problems in areas with low population density and proposing high population density zones, the integrity of the network is ensured, and potential hazards resulting from uneven distribution of energy are eliminated.

By efficiently controlling the distribution of PV systems, GIS technology could be integrated into these spatial studies to give vital information for optimizing PV network planning, increasing efficiency, and guaranteeing safety.

3.2.2. Temporal analysis

The safety of distribution network is enhanced immensely due to application of LSTM network and pattern recognition techniques for temporal analysis of photovoltaic (PV) generation.

The adopted LSTM network yields high prediction accuracy for PV generation and the control of energy to secure utilization of the grid. The forecasted time of maximum generation, as well as the daily generation rate, gives an assurance that the distribution network is viable enough to handle different inputs as far as energy is concerned in order to avoid an overload. It also reduces the frequencies of purchasing equipment with defects and in addition, it enhances the stability of the network.These fluctuations imply that the different cyclicities of energy production such as daily, seasonal, and annual cyclicities of the PV generation needs to be identified. Thus, awareness of the hours of the day to high generation plus hours of fluctuating generation result in improvement of schedules and plans of generation. Such knowledge is helpful to prevent problems mainly connection with instability and security in the network and to ensure that the distribution network will get ready to accommodate the fluctuations in the PV generation targets. Taken together, all these analyses help to ensure that the protection of the distribution network is above the acceptable threshold and that overloading and, therefore, stability problems are eliminated.

3.2.2.1. Long Short-Term Memory (LSTM)

Since the RNN is unable to extract long-term memories, the LSTM system uses an upgraded RNN method instead. However, with the aid of a memory cell unit, LSTM is capable of storing both short- and long-term data. In addition, the input, output, and forget gates are the three gates that the LSTM uses to function. The input gate first supplies the hidden layer with chronological data from the past and present. After that, a forget gate was used to collect the data required for additional processing.

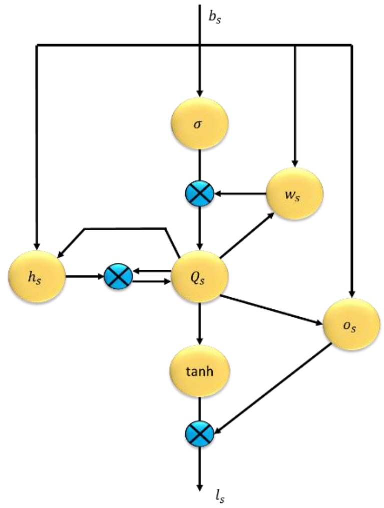

Figure 2: Block diagram of LSTM

Ultimately, the data is stored in the output gate and fed into the extra layer. Figure 2 illustrates how the specified gates manage the block's memory cell. Given that the hidden layer state is defined as $(n_1, n_2, \ldots, n_m)$ and the input sequence as$(b_1, b_2, \ldots., b_m)$, the following equations can be used to estimate the values of each gate function at time s.

$$w_s = \sigma(t_w l_{s-1} + v_w b_s) \tag{3}$$

$$h_s = \sigma(t_h l_{s-1} + v_h b_s) \tag{4}$$

$$Q_s = h_s \times Q_{s-1} + w_s \times \tanh\left(t_Q l_{s-1} + v_Q b_s\right) \tag{5}$$

$$o_s = \sigma(t_o l_{s-1} + v_o b_s + u_o Q_s) \tag{6}$$

$$l_s = o_s \times \tanh(Q_s) \tag{7}$$

The value entered is symbolized by w_s, the memory cell by Q_s, the output of the layer before it is displayed byl_{s-1}, the input values indicate the present input, h_s indicates the forget gate value, and o_s specifies the output gate value. Additionally, the block's output is indicated byl_s, and the weight bias is shown by t, v, and u. In the present scenario, tanhand are regarded as the activation function.

3.3 Load flow analysis (LFA) and dynamic stability assessment

To emulate this study, the following advanced analytical tools were used: It is a technique performed to determine the impact of PV production along with the consequences on the voltage levels, power flows, and shared losses. Furthermore, fault condition simulations were also performed to analyze the conditions of the network with disturbances of some types. The dynamic stability assessment involved temporal and spatial variables to give comprehensive characteristics of the network concerning various situations. This involved the ability to find sources of instability and assess potential problems, the formulation of stability limits as well as quantification of potential responses, and the general ability to look at the network in terms of performance and robustness simultaneously.

4. RESULT AND DISCUSSION

We used Matlab (R2022b) running Windows 11 to implement our approach. With a powerful ability to run challenging machine learning applications, the system is powered by an Intel Core i7 processor and has an IRIS graphics card.

Three primary categories were established when the data were gathered.PV data included details like location, latitude, longitude, capacity (kW), installation date, and tilt angle (degrees). Network data comprised information on peak load (kW), average load (kW), the count of feeder lines, historical incident dates, incident descriptions, and outage durations (hours). Environment data featured location, latitude, longitude, date, solar irradiance (W/m²), temperature (°C), and cloud cover (%).

4.1. Spatial analysis result

Spatial autocorrelation and clustering analyses reveal patterns in PV system distribution. Moran's I indicates moderate clustering, while Geary's C shows localized grouping. DBSCAN highlights dense clusters and isolated installations in the PV system distribution. This analysis aids in optimizing PV network planning.

4.1.1. Spatial Autocorrelation Analysis

Spatial autocorrelation evaluation is the degree to which the presence or characteristics of PV systems in one location are similar to those in nearby locations. For this analysis, two key statistics were evaluated: Geary's C and Moran's I.

- **Moran's I** is a measure of overall spatial autocorrelation. In this case, a Moran's I value of 0.35 was obtained, indicating moderate spatial clustering of PV systems. This suggests that nearby locations tend to have similar levels of PV system characteristics, such as capacity and daily generation, showing some degree of spatial dependence.
- **Geary's C**, another measure of spatial autocorrelation, yielded a value of 0.85. Since this value is <1, it indicates localized clustering. This means that the PV systems are more clustered in certain areas rather than being evenly distributed across the entire region. Nearby areas exhibit more similar characteristics compared to those farther apart.The results of the spatial autocorrelation analysis are shown in Table 1.

Table 1: *Result of Spatial Autocorrelation Analysis*

Statistic	Value	Interpretation
Moran's I	0.35	Moderate spatial clustering
Geary's C	0.85	Localized clustering; values < 1 indicate clustering

4.1.2. Clustering Analysis

The clustering analyses are performed by DBSCAN, providing different insights into the spatial distribution of PV systems. DBSCAN identifies clusters based on density and can also detect noise points. The DBSCAN analysis identified:

- **Cluster 1**, comprising a few residential areas in datasets6, 7, and 8, shows high density with substantial capacity and daily generation, indicating significant clustering of PV systems in these areas.
- **Noise** includes a few residential Areas in the dataset 1, 2, 3, 4, 5, 9, and 10. These areas are characterized by sparse distribution of PV systems, suggesting that they are less densely populated or isolated from major clusters.The findings of the clustering analysis are shown in Table 2.

Table 2: *Result of Clustering Analysis*

Cluster	PV System IDs	Capacity (kW)	Daily Generation (kWh)	Interpretation
Cluster 1	6, 7, 8	High	High	High-density clusters with significant energy production.
Noise	1, 2, 3, 4, 5, 9, 10	Varies	Varies	Less dense or isolated areas, with scattered or lower concentrations of PV systems.

According to the results of the spatial autocorrelation, the distribution of PV systems is moderately clustered since localized areas are found to have higher densities. The clustering analysis takes it a step further and defines particular areas as high-density areas, areas of medium or low density, or even completely void of such concentrations. This knowledge can be useful for foreseeing the distribution tendencies and potential network problems or possibilities for the installation of more PV systems.

4.2. Temporal Analysis Results

The temporal analysis results indicate the daily generation profile, monthly fluctuations, and even yearly trends of PV. Trends depict daily characteristics, massive variations with seasons, and annual trends implying the need for energy management and the effects of generation changes on the stability of the network.

4.2.1. LSTM Network Results

An overview of the predictive model's performance metrics for predicting photovoltaic (PV) generation is given in Table 3. The model appears to function fairly well, with predictions that are reasonably near to the actual data, as indicated by the validation loss of 0.35, which is expressed as mean squared error and is the mean squared discrepancy among anticipated and observed PV output levels. Short-term scheduling and making choices on energy management and grid integration are made possible by the seven-day forecast horizon. The model is shown to be highly accurate; it has an accuracy of a 90%, meaning it provides good predictions. The daily generation is at its highest between 11:00 AM and 1:00 PM which is the typical solar generation time. Finally, a simple indicator that is widely used to evaluate the daily efficiency of the PV system is presented with the help of the data demonstrating the average daily generation of 5.5 kWh. These points manifest the reliability, efficiency, and forecasting ability of the PV system of the model in one go.

Table 3: *Performance metrics*

Metric	Value
Validation Loss	0.35 (mean squared error)
Forecast Horizon	7 days
Accuracy	90%
Peak Generation Time	11:00 AM - 1:00 PM
Average Daily Generation	5.5 kWh

4.2.1.1. Pattern Recognition

These are contained in the smoothing of the graph of the PV generation as shown by the LSTM network below The PV generation patterns over different periods were analyzed using the LSTM network. According to the findings, the most optimal period to generate energy is mid-morning between 11am and 1pm because maximum daily PV generation is usually around this time at an average output of 5. 5 kWh. A specific seasonal analysis shows that the current PV generation jumps significantly during the summer, to about 7. Five kWh a day with the prior consumption being 3. Two kilowatt-hours per day in the winter. This change of seasons underlines the fact that energy managing plans have to be changed every now and then in a year. The increase of PV generation from January to July in an annual scale them shows a 20% rise in energy production, which portrays the variation in energy production from the start of the year to the mid of the year. Moreover, LSTM network is indicative of the correlation between the decreasing of winter PV generation and the increasing of network instability frequency, as well as the increasing of summer PV generation and the decreasing of network stability problem frequency. Understandings of these correlations are important in assessing the effects of PV production variations on the reliability of the network as well as organizing regular maintenance and upgrade properly. Table 4 below presents the results of performing pattern recognition from the previous step Using the chosen SSVEP frequency band for a participant, pattern recognition results were conducted. The generation per day of Solar power is illustrated in figure 3.

Table 4: *Result of Pattern Recognition*

Pattern Type	Metric	Value

Daily Patterns	Peak Generation Time	11:00 AM - 1:00 PM
	Average Daily Generation	5.5 kWh
Seasonal Patterns	Summer Generation	7.5 kWh/day
	Winter Generation	3.2 kWh/day
	Seasonal Variation	50% higher in summer compared to winter
Annual Patterns	Annual Variation	20% increase from January to July
	Correlation with Network Incidents	Fewer stability issues during high-generation periods; increased incidents during low-generation periods

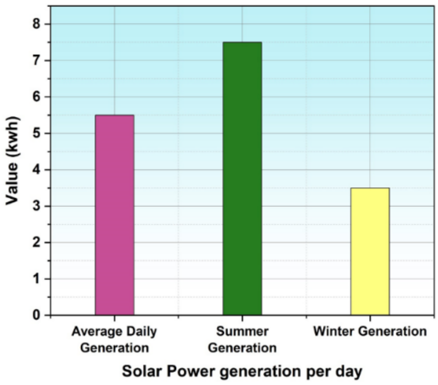

Figure 3: *Result of solar power generation in a day*

4.3. Load flow analysis

Therefore, the spatial distribution and the temporal generation pattern of the PV system data must be integrated for using the spatial-temporal results in the load flow analysis. To consider and analyze these elements' impact on the load flow, the MATLAB simulations were employed.

In this case, we used the MATLAB simulations to analyze the voltage profiles, power flows, and power losses of network in the load flow analysis concerning different photovoltaic (PV) generation stages. The examination included scenario comparison where PV penetration was at 10%, 20%, 30%, 40% and 50%, steady state situation modeling was used techniques such as the Newton- Raphson technique. Through MATLAB simulations, it is shown that the average voltage decreases across the network as the penetration level increases, which indicates potential problems in voltage management. For example, when PV penetration level is at 10%, the average voltage can be 234. 6 per cent to 8 V in the DPC-treated rats, which is 228.5 when V is normal. 5 V at a loading of 50%. The result of the average voltage is presented in the figure 4 below. As the voltage drops at 10% PV penetration, the flow of the power is 585 kw, while at 50% penetration from the grid and increased losses it is reduced to 525 kw. In formulating the power flow findings, the following figure was used as presented in figure 5. The power losses increase to 8. From 5 kW of electricity at 10% of the usage level to 10 kW, electrical equipment is offered. Five kilowatts at fifty percent penetration. Figure 6 it implies the same even if the outcomes of these power losses are considered.

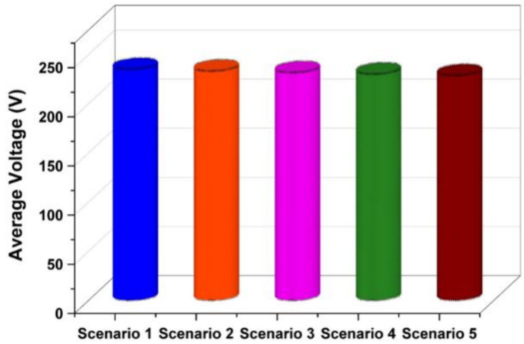

Figure 4: *Result of Average Voltage (V)*

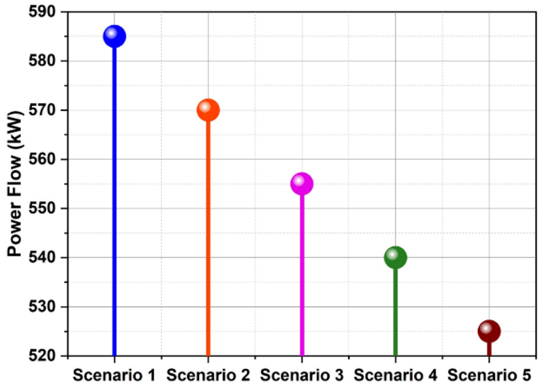

Figure 5: *Result of Power Flow (kW)*

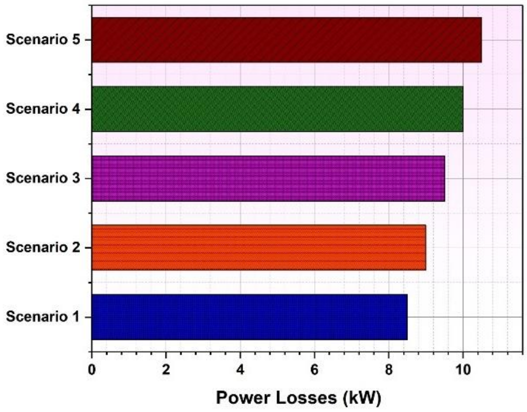

Figure 6: *Result of Power Losses (kW)*

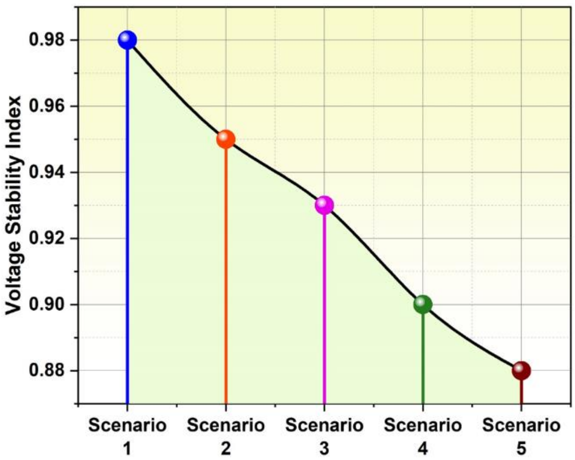

Figure 7: *Result of Voltage Stability Index*

The voltage stability index also declines with higher PV penetration, suggesting reduced voltage stability. This index falls from 0.98 at 10% penetration to 0.88 at 50%, highlighting the potential for voltage regulation issues. Figure 7 shows the result of the voltage stability index. Integrating spatial and temporal data into this analysis, we considered the geographic distribution of PV systems and their generation patterns. Areas with higher PV capacity and varying daily and seasonal generation levels were analyzed to understand their impact on voltage and power flow. It offers insights into how PV integration impacts network performance and aids in the identification of possible problems with voltage stability and power losses. It is made possible using MATLAB simulations. The outcomes of the load flow study using the data that was provided and displayed in Table 5:

Table 5: *Load Flow Analysis for Different PV Penetration Scenarios*

Scenario	PV Penetration Level	Average Voltage (V)	Power Flow (kW)	Power Losses (kW)	Voltage Stability Index
Base Case	0%	235.4	600	8.0	1.00
Scenario 1	10%	234.8	585	8.5	0.98
Scenario 2	20%	233.0	570	9.0	0.95
Scenario 3	30%	231.5	555	9.5	0.93
Scenario 4	40%	230.0	540	10.0	0.90
Scenario 5	50%	228.5	525	10.5	0.88

4.4. Dynamic Stability Assessment Results

To measure the impacts of fault circumstances on the power system, these conditions were simulated in this research. Transformer failure cases described power outage situations with alternative conditions ranging from no issues with power delivery system to substation transformer faults, feeder line failure at particular sites. At the same time, feeder line damage focused on the examination of equipment failures that occurred in different substations. Such exercises assisted in improving perception of the given network and its response to such interferences by making one realize how much different types of defects affect the network's robustness, speed, and reliability. The findings of the dynamic stability assessment are presented in Table 6 below.

Table 6: *Results of Dynamic Stability Assessment*

Fault Condition	Substation ID	Voltage Drop (V)	Frequency Deviation (Hz)	System Response Time (s)	Recovery Time (s)	Network Stability Index
Baseline	-	0.0	0.0	0.0	0.0	1.00
Transformer Failure	1, 2, 3, 4, 5, 8	13.5 - 18.7	0.4 - 0.6	1.5 - 2.5	9.0 - 15.0	0.82 - 0.88
Feeder Line Damage	6, 7, 9	10.0 - 14.2	0.3 - 0.5	2.0 - 3.0	7.0 - 12.0	0.85 - 0.89

4.4.1 Transformer Failure

Transformer failure illustrated a lot of effects on the simulation of the unstability of the network. Inadequate and failure of Substation transformers led to voltage fluctuations of about 13. 5 and 18. 7 volts which was very much stressing the network and possibly would have caused voltage instability. These faults demonstrated changes in the frequency of occurrence from 0 to 0.4 Hz to 0.6 Hz that implied disturbance of the network's working frequency. The response time of the network to some of these malfunctions is between 1 in the case of their occurrence. 1.5 to 2.5 seconds, which signifies what kind of speed the network begins fixing problems from a client's viewpoint. Another cause of variability was the recovery times, or in other words the time it took to return to normal functioning as captured below; The variability in the recovery times was as a follows; 9. 0 to 15.0 seconds, this raises a concern of the time it takes for the system to stabilize after experiencing a transformer failure. The indices of the network stability ranged between 0 and 0.82 and 0.88 during these faults, pointing out decrease in stabilities during these periods and evidently indicating the large influence of transformer failures on the network's performance.

4.4.2 Feeder Line Damage

Apparently, moderate effect was distinguished when feeder line damage simulations were compared to transformer failures on network stability. Though it influenced the voltage profile, voltage drop resulting from damage on the feeder line was different ranging from 10. 0V to 14. 0.2V which was not as steep as the voltage drops that came with failures in the transformer. The variations of the frequencies during feeder line faults were different and ranged from 0.3 Hz and 0.5 Hz, which was not as high as in the cases associated with transformer issues, and, therefore, the disturbances were not as significant. Compared with transformer failures, the response time of the system to damage to the feeder line was between 2.0 and 3.0 seconds Recovery times ranged from 7.0 to 12.0 seconds, indicating comparatively faster network stabilization. When considering feeder line damage, the network stability index varied from 0.85 to 0.89, indicating a somewhat higher level of resilience to feeder line faults than when considering transformer failures.

From the analysis, it can be observed that transformer faults result in a relatively large reduction in voltage and frequency deviations as compared to feeder line faults. The reaction of the network to such transformer failures is slower and generally takes more time to come to normal, showing the effect it has on the stability of the system. The feeder line damages more often that disturbs the voltage and frequency to a lesser extent and recover at a faster speed than the distribution line damages. This holistic assessment assists in comprehending the network tolerance level and finding out the gaps in fault management and healing procedures.

These analyses' outcomes provide the conclusion on the safety of the distribution network with the assessment of the influence of PV generation. The benefits of time series and mapping are to present the patterns and areas of increased PV penetration and the load flow analysis demonstrates issues with a high amount of feed-in PV current, while fault analysis reveals that the network is more sensitive to various types of faults. They are useful in determining the performance level of the network and enhancing the reliability and safe distribution of the network.

5. CONCLUSION

Lastly, this work provides a detailed exploration of the interfacing issues of PV systems with distribution networks in terms of stability and safety.With the help of mathematical modeling coupled with spatial and temporal assessment of the network performance, the effects of PV generation were considered. The spatial analysis showed that the degree of clustering was rather average and found high-density spots, which are vital for demand management, with the help of the temporal analysis, the generators' working hours and their patterns within a year were indicated. Load flow analysis showed how voltage, power flow, and stability are influenced by fluctuating PV contributions, with a special focus on the hardships when the PV injected is high. Other dynamic stability assessments additionally regarding the network reliability in the case of faults highlighted the more considerable effects of transformer failures than feeder line damage. It is worthwhile to understand the opportunities for improving the integration of PV systems, reviewing and improving methods of response to faults, and guaranteeing the increase in the share of renewable energy and reliability of distribution networks. Therefore, the effectiveness of the spatio-temporal analysis depends on the resolution of the geographic and temporal data. Low resolution may hinder the clear identification of important details and is likely to compromise the accuracy of the analysis. The follow-up studies should aim at increasing the spatial and temporal density of data sampling and processing. Sophisticated sensors and high-accuracy geographic information systems may give detailed information and results of spatial and temporal analysis in distribution networks, which may be more accurate and precise.

Funding :
State Grid Shaanxi Electric Power Co., Ltd. Science and Technology Project Funding (Project No. 5226JY24000C)

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