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An innovative fast iterative process algorithm computerization for intermittency LSSPV generation reconfiguration

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ABSTRACT

The recent implementation of solar photovoltaic (SPV) power generation in low-voltage distribution networks has increased due to its environmentally friendly technology, low cost, and high efficiency. However, SPV generation carried both the availability of uncertainty and intermittency on power energy exceeding voltage range, increased losses during reverse power flow action, and energy transmission problems. This paper presents a new capabilities methodology with accurate analysis to simulate the intermittent nature of SPV energy including normal generators associated with uncertain customer demand of high resolution with 1-minute temporal resolution using a fast iterative process algorithm (FIPA) simulated by Python programming. The primary goal is to address the unpredictable nature of SPV using computer operation technology connected to a real network with a fast iteration process. The result shows that in 0-10% of standard generators, grid energy (GE) is still required in daily supply, and the intermittent nature influences voltage violations and losses. Besides, the prediction typical SPV method (zero fluctuation) can serve as guidelines for engineers to design the photovoltaic (PV) module reducing its fluctuating nature and battery installation area. The research provides utilities with accurate information to plan for various difficulties at different levels of PV penetration while reducing time, effort, and resource utilization.

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1. INTRODUCTION

The conversion of solar energy into electrical power through photovoltaic (PV) panels is a cornerstone in the advancement of renewable energy sources (RES), due to its viability in regions with high solar irradiation and the benefits of low maintenance and installation ease. As a result, people are motivated to participate in the SE connection to contribute to energy exchanges and gain revenue [1]. In the Middle East, where solar irradiation is excellent, it is possible to use solar energy to allocate power solar to large deserts [2]. With this change, the economic strategy can be enhanced by supplying SE usage to rural and urban lives. The inherent variability of solar irradiation leads to fluctuations in the power output, which, if not managed adeptly, can precipitate voltage instability and transformer overloading, compromising the reliability of the power supply. This will ensure a seamless and uninterrupted supply of energy, thereby promoting efficiency and reliability in the system.

Previous studies have explored the solar photovoltaic (SPV) model's influence on grid stability, recognizing the risk of voltage fluctuations as solar power generation scales up [3]. These studies often ignored load uncertainties and PV large-scale solar photovoltaic (LSSPV) system transients under various operational situations. As SPV penetration increases, its intermittency also affects voltage fluctuation [4], [5]. The author claims that weather and climate affect wind and solar PV systems, causing unstable voltage, transformer overloading, and other operational concerns [6]. To address these concerns, the author developed a system model limited to critical time points and should note that the results do not incorporate the range determination of essential parameters such as voltage bus and losses. Heslop *et al.* [7] emphasize overvoltage limit as their primary integration factor, as they discovered voltage rise and unbalance in distribution networks due to PV penetration. This risk has become more challenging to mitigate since LSSPV panels were added to the distribution feeder. The simulation was constrained to a constant load or generator for a specific case in the previous study. It is a technique that is far from the reality of the problem and can produce inaccurate results. This new research examines how PV intermittency might be included in real networks under overall time interval constraints, including load, generator, and LSSPV uncertainty.

The process of machine learning involves the analysis of training datasets using classification and regression techniques. This approach affords the ability to extract insights and make predictions from complex data sets, leading to advancements in a variety of fields such as medicine [8], transportation [9], finance, and engineering [10]. Bukar *et al.* [11] seek to bridge these gaps by proposing a novel model that not only anticipates but also acclimatizes to the fluctuating nature of solar and wind energy generation. Their approach leverages advanced machine learning techniques including the grasshopper optimization algorithm (GOA) and the hidden Markov model (HMM) to optimize and predict energy output under a variety of weather scenarios, with a specific not focus on intermittency [12]. Our model uses real-time uncertainty wide range, which is different from previous research that often assumes static load conditions or neglects the full scope of PV output fluctuations. Past research has utilized various machine learning techniques to accomplish the objective, but they do not evaluate the system for ideal LSSPV output power (no fluctuation in RES).

Past established algorithm techniques can also assist in managing energy storage to lower costs [13] and manage the functioning of electric vehicles [14]. Historically, research has focused on enhancing the problem with a fixed load state. Nevertheless, priority should be given to load uncertainty and intermittent SPV generation. According to an article by Torquato *et al.* [15], SPV generation performance can cause overvoltage in a network. Besides, previous research has only considered single simulations and neglected load uncertainties. Bougouffa and Chaghi [16] simulate a network to estimate the optimal relays' pickup current (Ip) and time dial setting (TDS) using PSO to find the Pbest fitness value. However, the simulation has some limitations. It does not consider the fluctuation of RES and the uncertainty of electrical demands.

There are three types of stability: steady state, transient, and dynamic. This research focuses primarily on steady-state simulation systems using the PSS@E and Python programming languages. The methodology was validated using the IEEE 39 bus system with real LSSPV data from Malaysia to forecast typical SPV (TYP) generation units with limited information required. The paper is divided into numerous sections. Section 2 outlines the problem formulation for this investigation. Section 3 outlines the proposed method for obtaining the TYP profile and the overall methodology used in this paper. Section 4 examines the simulation results and compares various PV fluctuations. Section 5 closes by discussing the potential ramifications of the findings given in this study.

2. PROBLEM FORMULATION ANALYSIS

2.1 The formulation forecast: typical LSSPV profile (TYP)

This section presents the new novel mathematical method that progresses from fundamentals to developing the optimal LSSPV profile called TYP that can be employed in network analysis. In this study, a particular nation's SPV system, which is in Malaysia, is utilized. Figure 1 illustrates the fundamental LSSPV system process utilized in this study. Iskandar *et al.* [17] the fundamental principle of PV plants are discussed with an average range of solar radiation values between 0 and 8 KW/m2. The cost of the system, the type of solar cell, the length of the warranty, and the installed power in Watts are the most important aspects to consider when choosing PV panels. The effectiveness of the SPV system is dependent upon the proper installation of its components. The PV modules were fixed at a 10-degree angle of incline facing south. Generally, an SPV system is divided into two sections, photovoltaic DC input, and photovoltaic AC output, and integrates the energy into the grid through a step-up transformer. The energy started from sunlight hits the PV array to proceed to the power optimizer and maximum power tracking (MPPT) control provides functioning to maximize and improve the DC power generation [18]. This MPPT algorithm measures the solar operating voltage by adjusting the impedance or getting near the maximum power point (MPP), after which the DC-to-AC inverter converts the DC solar power into AC power. The electricity produced by a PV system is connected to the utility grid and sold to the utility provider at retail price.

Inclination, azimuth, and local zenith are all displayed in Figure 2. The global horizontal irradiance (GHI) is derived from the total shortwave irradiance accumulated from horizontal parallel PV to the ground, including direct and diffuse irradiance. GHI is the most significant parameter for estimating PV radiance performance. The expression for GHI is (1).

$$GHI = DNI \times Cos\ (\theta) + DHI \tag{1}$$

Where DNI is direct horizontal irradiance, DHI is diffused horizontal irradiance, and θ is local solar zenith angle.

According to the researcher, the electricity produced by SPV is highly dependent on specific shading and insolation conditions, like the global, normal, and diffuse horizontal irradiance [19], [20]. Salamalikis *et al.* [21], the histogram of the global clearness index in GHI was unimodal, with a substantially skewed peak. The ratio of GHI to solar irradiance is the global clearness index. The most excellent daily pattern that can be generated by PV irradiation is the GHI. To achieve the best SPV profile, it's necessary to convert DHI into a cos function [22]. Therefore, a new novel method has been devised to generate a standard pattern for SPV power production to yield the maximum possible irradiation. According to the (1), the new optimal method for obtaining the TYP formula is (2).

$$TYP = \sum_{i=M}^{N} PE\ co\ s(\theta) + cos\ \ (90^{o}) \tag{2}$$

Whereas M and N are morning and evening time intervals with a temporal resolution of 1-minute, PE is the maximum yearly performance of the PV generation system, and the derived formula is visualized as a red line in Figure 3. The figure illustrates the ideal performance metric with no fluctuations. The fast iterative process algorithm (FIPA) process will evaluate this profile to provide a comprehensive analysis of its capabilities.

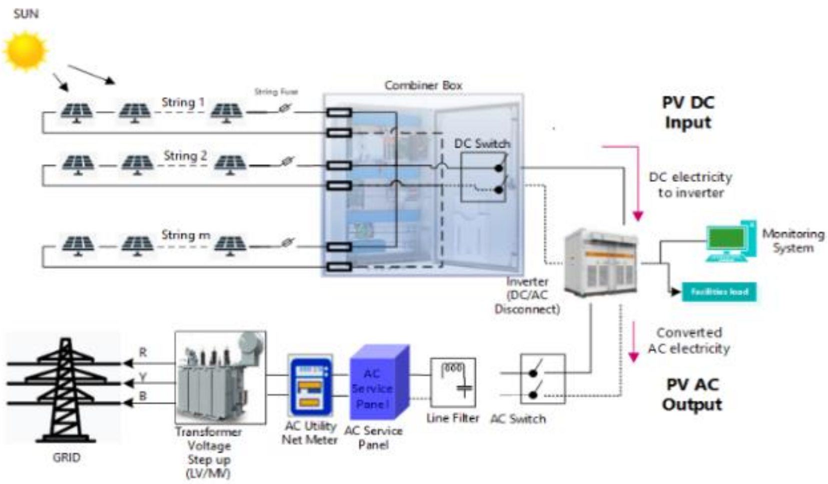

Figure 1. The schematic diagram for LSSPV in Malaysia

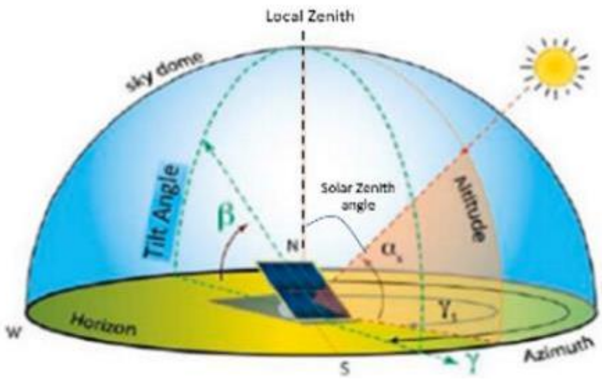

Figure 2. Reality of solar tilt, azimuth angle, and solar zenith angle orientation

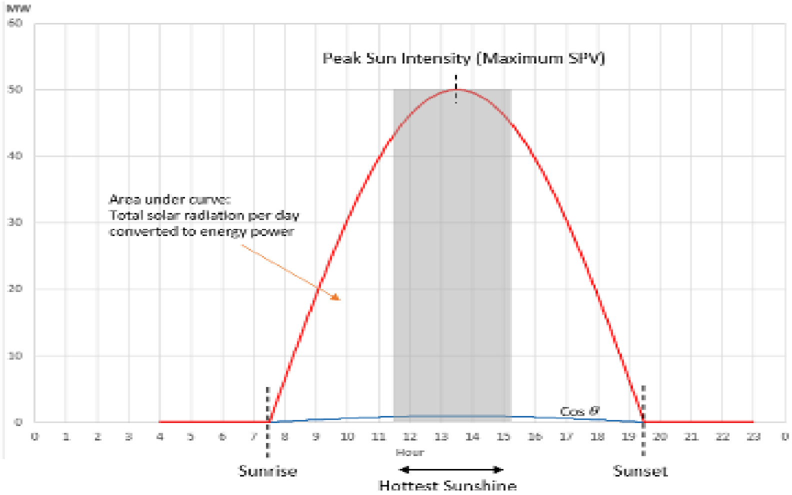

Figure 3. New typical daily SPV generation (TYP) forecasted suitable used in simulation network

3. METHODOLOGY

The data sourced from East West in Malaysia was utilized. The LSSPV generation was obtained from a specific location in Malaysia; they were sent to the grid managed by a utility provider in Malaysia. Figure 4 illustrates the comparison of the PV output power generation performance with a typical SPV used in this study. The perfect LSSPV with zero fluctuation (TYP) profile is a newly developed forecast that utilizes a formula presented in (2). If the solar irradiation decreases, the PV production also decreases accordingly. The LSSPV output appears to have fluctuating power output between 9:30 a.m. and 2:40 p.m. on critical time intervals. Figure 5 depicts the process of FIPA implemented in this work. FIPA is executing regarding SPV penetration fluctuation rate for every point of 1-minute temporal resolution and varies with load demand. In this investigation, LSSPV is connected to the IEEE 39 bus system via bus 32 for initial condition. Firstly, the chosen bus system should be improved by adding a shunt capacitor, checking the stability [23], and improving the voltage limit. The SPV generator, other normal generation, load, and control equipment are connected simultaneously. Secondly, the stability network will go through the FIPA process to initialize the constant path of PSS@E. In this novel method, a set of power flow analyses will be conducted repetitively regarding LSSPV condition curves and uncertainty load demand. It will execute the process repetitively and complete the rotation process within a mere 1-minute timeframe. The system then records the outcome for each time frame interval. The analysis was conducted to evaluate electrical energy performance, specifically in relation to load requirements. Additionally, the study will evaluate the performance of standard SPV generation under different load levels. Besides, the simulation utilizes a basic LSSPV without intermittent features (TYP) for comparison. This development presents a significant advantage, as it facilitates the process for planning engineers to test and apply RES applications into the network, thereby enhancing performance and improving the overall efficiency of the network.

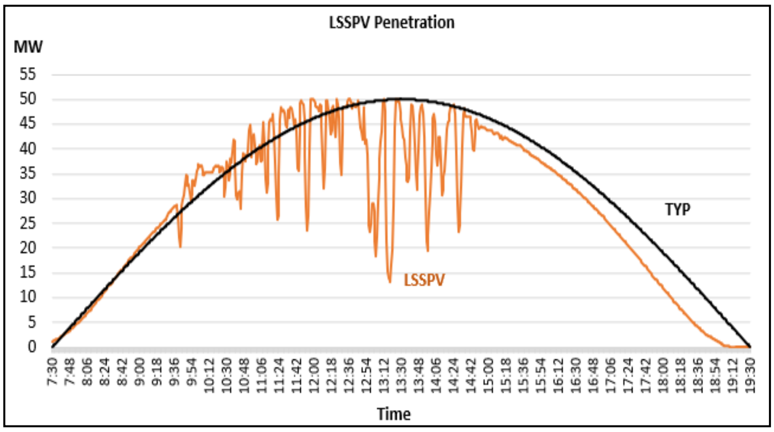

Figure 4. Profiles for typical (TYP) and LSSPV generation

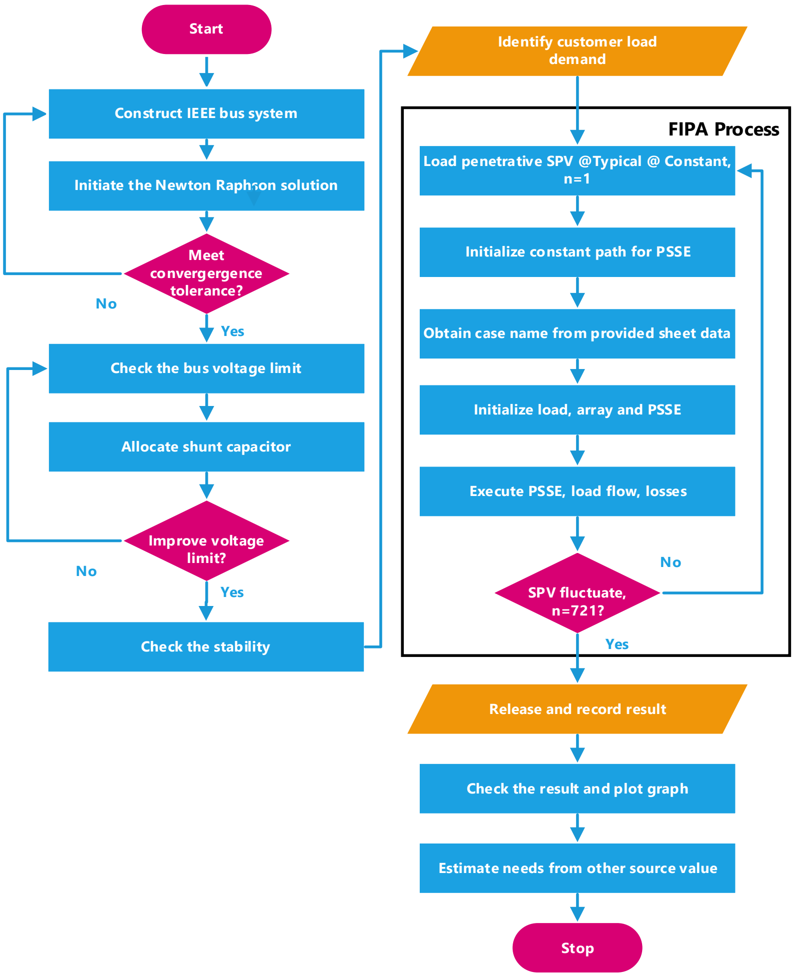

Figure 2. Research roadmap implemented

The Python algorithm automates the LSSPV penetration profile, while the system simulates the network database using PSSE software. Power transactions, parameter data, and electrical demand are input to the algorithm. Power flow is completed at various times in the network within allowable voltage limits. The simulation returns load flow, bus voltage, power loss, and additional measurement data. The data was processed between 7.30 a.m. and 7.30 p.m. with intermittent input power. This method processes numerous quantities of high-resolution one-minute interval data concurrently with the network's energy demand. The FIPA serves as the bridge test simulation system, and the software simulation serves as a superior design for connecting multiple real-time data simulations. The research code details of this study have been uploaded into Mendeley Data [24].

4. RESULTS AND DISCUSSION

4.1. Measurement, sensitivity, and statistical analysis

In this study, the energy performance of LSSPVs in proportion to network demand was examined using the FIPA algorithm in a time domain analysis, which may be implemented in the smart cities area of technologies. The results of the simulation, specifically regarding load requirements, were captured in Figure 6, considering LSSPV fluctuation used in this analysis process. There are two distinct categories of energy generation losses: typical LSSPV generation and constant generation, where the results are represented in Figures 7 and 8, respectively. The maximum loss occurs at 55 MW for LSSPV with fluctuation, 47 MW for standard SPV, and 40 MW for normal GE. The total amount of energy lost for fluctuation LSSPV above was 44,4406.08 MW, corresponding to a loss index of 1.301%. It has a high loss index compared to the typical and constant power. This is because we are considering fluctuations in the conditions of the LSSPV simulation. These visual aids illustrate the higher fluctuation in normal daily energy LSSPV will bring high energy loss incurred during production.

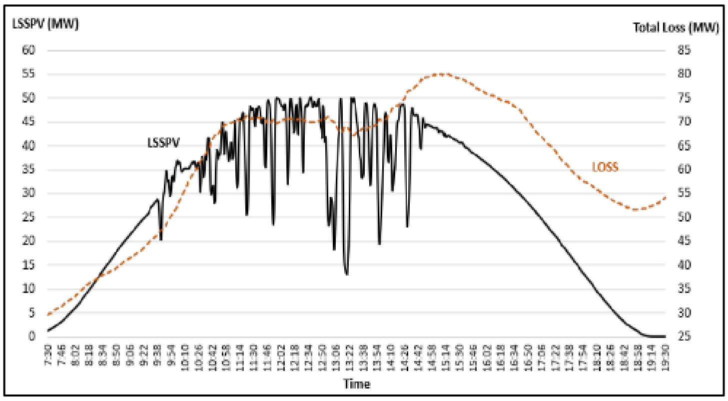

Figure 3. LSSPV and its losses in profile pattern

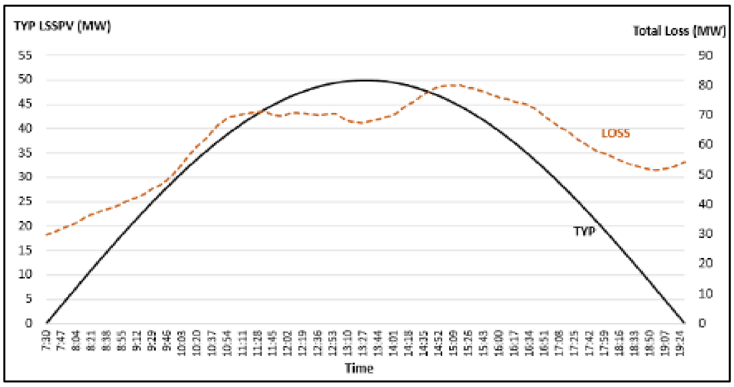

Figure 7. TYP profile integrated and the result of losses

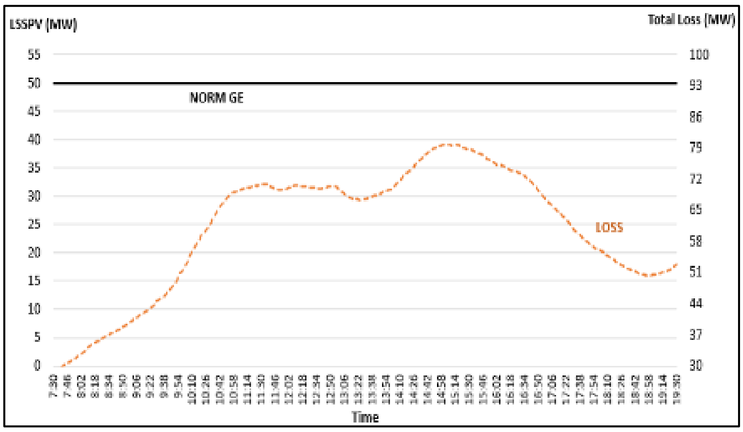

Figure 8. Nominal constant generator 50 MW integrated at bus two and the result of losses

The result of the network analysis for LSSPV fluctuation revealed that there is a potential for the voltage per unit to become less than an accepted limit during a critical time interval. Besides, reverse power flow is a common issue that occurs during critical times of SPV generator performance where critical time interval occurs between 11 a.m. and 2 p.m. This study examines all the buses in the network. However, this paper represents only buses like 6, 12, 20, and 25 due to space constraints. Figure 9 demonstrates the voltage of several buses fluctuates significantly from sunrise to sunset impacted by LSSPV intermittent. The result shows that the voltage fluctuations increase at a range of intermittencies that occur in this LSSPV generation. A significant optimal pattern of TYP prediction with superior results to others has been identified. When the power generation exceeds the average action with varying intermittent, the voltage magnitude will become unstable during that session. This can be seen in Figure 10, where the input from the SPV generation pattern controls the voltage instability during critical time intervals.

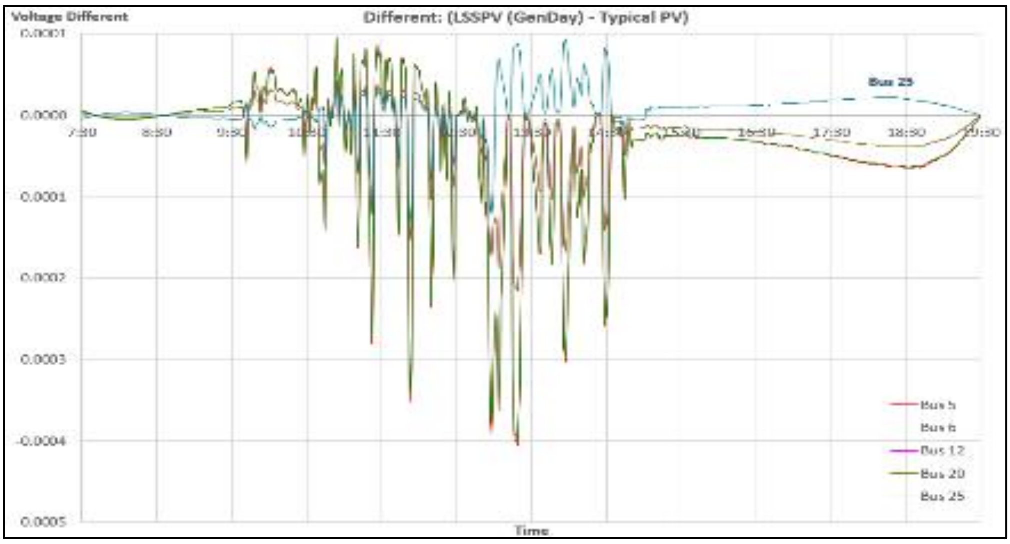

Figure 4. Difference voltage fluctuation occurs between LSSPV and typical SPV

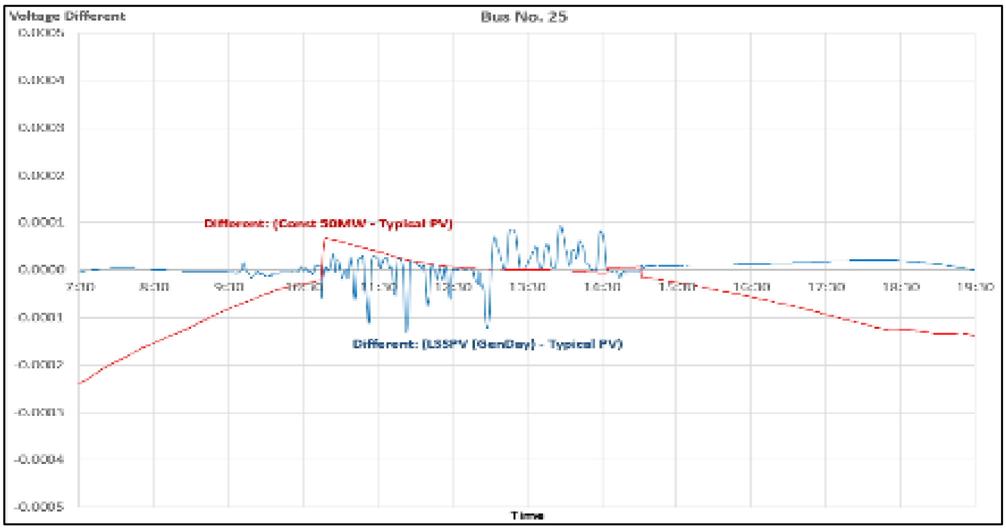

Figure 5. Different voltage conditions at bus 25

Table 1 displays the results of a statistical analysis conducted on two different energy sources, TYP and LSSPV. The data collected has been thoroughly analyzed and presented in a comprehensive table for interpretation and comparison. Table 1 shows the mean, median, standard deviation, and variance values for both sources, which are almost similar. The central tendency measures, mean and median, are almost identical for both distributions. The result indicates that both sources follow a symmetrical normal distribution pattern. It can be concluded that the TYP formula accurately represents a perfect condition of LSSPV.

The results of a statistical regression analysis exploring the correlation between TYP and LSSPV are presented in Table 2. To analyze the measurement error of multiple R, R square, adjusted R square, standard error, mean absolute error (MAE), and mean absolute percentage error (MAPE), the results were assessed, with values closer to zero being better. The root mean square error (RMSE) is 7.345, indicating that the TYP fits the dataset perfectly. Additionally, the multiple R, R square and adjusted R square values were found to be 0.914, 0.835, and 0.834, respectively. These values being closer to 1, indicate that the TYP profile is in good condition. The results suggest that typical SPV generation can be used as an alternative for PV performance patterns in electrical simulation networks. Table 1. Statistical analysis on both TYP and LSSPV.

Table 1. Statistical analysis on both TYP and LSSPV

	TYP	LSSPV
Mean	31.7867898	28.20517406
Median	35.35533906	31.26
Standard Deviation	15.43362112	15.43533253
Sample Variance	238.196661	238.2494902
Kurtosis	-1.068135575	-1.101309814
Skewness	-0.497772591	-0.390650042
Range	50	50.145

Table 2. Regression analysis between TYP and SPV for 721 observations

Statistical regression between TYP and LSSPV	
Standard error	6.281902786
MAE	4.726817
MAPE	0.21351625
RMSE	7.34533
Multiple R	0.913562086
R square	0.834595684
Adjusted R square	0.834365637

4.2. Comparison analysis

In this section, the results demonstrate the comparison analysis between LSSPV, TYP, and no PV. The outcome shows some modest fluctuations from early morning, 10:42 a.m., through late afternoon, 3:30 p.m. The shape of losses is nearly identical in other hours. However, we cannot declare that the LSSPV is in good operating order because the percentage of extra assistance provided by other generators is considerable, as seen in the study results in Table 3. Within 12 hours, approximately 0-10.67% of other generators may be required to support the network. Standard generators are not necessary to feed the grid at noon when the maximum LSSPV can produce electricity. This table compares the output power of a continuous generator 50 MW and LSSPV. It was found that from 8-10% of the other generators need to collaborate with LSSPV in the morning and evening. At the peak of maximum irradiance, LSSPV continues to operate normally at the required demand. Due to the intermittent nature of SPV energy, this SE cannot work alone to meet the load demand.

Table 3. Time division based for both 50 MW and LSSPV at bus 2

	7:30 a.m.		12:00 p.m.		3:30 p.m.		7:00 p.m.	
Gen	Const, 50 MW	LSSPV, MW	Const, 50 MW	LSSPV, MW	Const, 50 MW	LSSPV, MW	Const, 50 MW	LSSPV, MW
30	200.579	202.957	271.329	271.340	297.812	298.262	261.669	264.067
31	442.590	447.836	598.703	598.727	657.141	658.133	577.389	582.680
32	50.000	1.166	50.000	49.778	50.000	40.770	50.000	0.750
33	481.390	487.096	651.189	651.215	714.750	715.828	628.006	633.761
34	387.786	392.383	524.569	524.590	575.771	576.639	505.894	510.529
35	494.762	500.627	669.278	669.305	734.604	735.712	645.451	651.365
36	427.902	432.974	578.835	578.858	635.333	636.292	558.227	563.343
37	414.530	419.444	560.746	560.769	615.479	616.408	540.783	545.738
38	601.738	608.870	813.987	814.019	893.437	894.785	785.007	792.201
39	668.597	676.523	904.429	904.466	992.708	994.206	872.230	880.223
Supplementary other gens (%)	10.670		0		0.93		8.25	
Supplementary other gens (%)	0-10.67% (From 7:30 a.m.-7:30 p.m.)							

Table 4 displays the results for TYP, LSSPV, and no PV to ensure precision and reliability in our data analysis. The prediction of TYP with no intermittent consists of the lowest losses and the best voltage deviation compared to the normal LSSPV profile. Table 4 shows the voltage magnitudes with LSSPV at each bus are not within the acceptable limit of 0.95-1.05 p.u. Some buses in the network are below the acceptance limit. The constant GE and typical SPV are the best options because they seem to have a reasonable voltage difference and low loss value, as shown in Table 4. As a result, the voltage limit is not achieved if these power demands with high fluctuation are provided into the network. The result also indicates that the TYP profile can keep the voltage within an acceptable range compared to LSSPV features. To enhance the performance of LSSPV within the network, it is recommended that intermittent should be minimized approaching to TYP profile. Without FIPA information would be limited and feared to be inaccurate. Based on previous studies, it has become clear that the simulation is limited in its scope and prone to inaccuracies if it does not incorporate FIPA. This suggests that the inclusion of FIPA in the simulation is essential for achieving more realistic and reliable results. It is essential to consider the inclusion of FIPA in any simulation to ensure an optimal outcome from the result.

According to Table 4, the network has 80.15 MW of total power losses when applying the LSSPV generator. Once the performance of LSSPV appears to vacillate, losses will increase, and the voltage will exceed the allowed level in the feeder distribution system. According to the results, the FIPA algorithm time interval model has attained the precision necessary to simulate electrical energy in the network. The established platform helps plan engineers and forecasters to predict the presence of time-dependent motivation plans, whereas many previous studies did not do so like the article in [25].

Table 2. Comparison results between TYP, LSSPV, and Const 50MW generator

		% Penetration	Min ploss (MW)	Max ploss (MW)	Total loss (MW)	Min qloss (MW)	Max qloss (Mvar)	% Loss index (within 12 h)	Max voltage, (pu)	Min voltage (pu)
Without FIPA		Not consider intermittency	71.61	71.61	2076.88	1343.3	1343.3	NA	0.950	0.861
With	TYP	100%	15.66	70.05	44,267.50	550.23	1.199	1.018	0.950	0.950
FIPA	Fluctuation	78%	18.780	80.15	45,446.08	550.01	1.301			
In	LSSPV							0.995	0.861	0.861
12h	Const	No SPV	18.780	69.91	43,034.35	490	1.197	1.040	0.975	0.975

5. CONCLUSION

From the above investigation, an accurate result can be obtained by considering the intermittent LSSPV in approaching uncertain energy demands. The specific load, PV generating conditions, and typical LSSPV curve pattern are established to estimate the uncertainty's impact on the distribution feeder. The FIPA is developed due to its flexibility, user-friendly interface, and speedy simulation outcomes in determining multiple parameters for each temporal resolution. There is no missing information parameter, preventing a deep analysis of the LSSPV performance throughout the network. Despite the limited information and rapid simulation, the entire network can be connected for each point of fluctuation case. We predict the typical output performance of the LSSPV profile as generator power up to 100% with zero fluctuation. This new TYP profile will serve as a benchmark for quality in future PV farms to design LSSPV with no fluctuation. Transforming the LSSPV profile into a TYP shape significantly reduces the loss of the overall network. Besides, the study proved that any high fluctuation range of SPV energy production resulted in voltage instability at that fluctuating range. This approach method promises to yield better accurate results compared to past studies. It has been observed recently that excluding FIPA may lead to imprecise and inaccurate results. The proposed method also can reduce the high probability of reverse power flow, which, in turn, can prevent damage to the protection system. Besides, the percentage of other standard generators supported in the overall network can also be determined. By accounting for the varying states of load and generator performance, and by providing a reliable topology of SPV profiles, this research contributes a significant piece to the puzzle of sustainable and resilient energy systems, paving the way for a future where renewable energy can be harnessed efficiently and reliably. Additionally, the TYP profile presented in this article can serve as a useful reference configuration for achieving a stable SPV output without fluctuations and mitigating uncertainty issues. With this proposed technique, the adaptable and resilient infrastructure can be improved, especially in the high variability of RES. Besides, this approach will enable utility providers, distributed generator teams, and financial departments to assess and address issues related to electricity prices and the quality of supply in the SPV sector. The integration of renewable energy into the generation and distribution system can achieve sustainability goals and address climate change.

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