Transport and Communications Science Journal, Vol. 76, Issue 04 (05/2024), 625-637

Transport and Communications Science Journal

AN OPTIMAL SOLUTION FOR INTEGRATING PV ENERGY SOURCES INTO THE DISTRIBUTION NETWORK

Tran Van Khoi*, An Thi Hoai Thu Anh

University of Transport and Communications, No 3 Cau Giay Street, Hanoi, Vietnam

ARTICLE INFO

TYPE: Research Article
Received: 12/06/2024
Revised: 15/01/2025
Accepted: 10/05/2025
Published online: 15/05/2025
https://doi.org/10.47869/tcsj.76.4.14

* *Corresponding author*
Email: tvkhoi.ktd @utc.edu.vn; Tel: 0971385813

Abstract. Vietnam, situated near the equator, receives high solar radiation, making it a crucial factor in addressing the urgent global shift to renewable energy sources. This transition aims to reduce CO_2 emissions and achieve carbon neutrality by 2050. In the context of effectively harnessing solar energy, this paper presents a solution for identifying the location and power of renewable energy systems integrated into the distribution network. The objective is to minimize transmission power loss and voltage fluctuations while maximizing profits. The proposed solution involves using the Newton-Raphson algorithm to determine energy distribution on the power network in specific scenarios. Subsequently, the Hill Climbing algorithm is applied to identify the optimal location for deploying the renewable energy system on the power network. Moreover, a method for determining the power of renewable energy systems is implemented to minimize the objective function utilizing the Newton method. Experimental validation on the IEEE 33 bus and 69 bus test systems demonstrates that the proposed methodology consistently achieves optimal results expediently, underscoring its efficacy.

Keywords: Renewable energy, distributed sources, energy management, loss minimization, voltage fluctuation, optimization algorithm.

1. INTRODUCTION

In the context of worsening climate change, fossil fuels are responsible for almost 75% of greenhouse gas emissions and approximately 90% of global CO_2 emissions. This has prompted a shift towards renewable energy sources such as solar, wind, wave, and bioenergy [1]. However, the intermittent nature of renewable energy generation poses economic and engineering challenges that limit their widespread adoption. Unlike traditional power plants, renewable energy facilities require specific high-resource locations [2]. To address these challenges, mathematical optimization tools are needed to assist in the planning and decision-making, particularly in determining the size and location of renewable energy plants. Distributed generation (DG) has emerged as a way to promote a more significant deployment of renewable energy by reducing large-scale investment costs and fostering competition in the renewable energy market.

In a liberalized electricity market, opportunities for development at distribution levels are increasing, particularly with optimized system placement. This can significantly mitigate technical challenges associated with renewable energy integration. By strategically allocating and determining the optimal capacity of renewable energy sources, losses in the power system can be reduced while enhancing voltage and network reliability. Electric utilities prioritize determining the maximum capacity of renewable energy that can be integrated into the system while minimizing losses. However, failure to appropriately locate and scale renewable energy sources can lead to increased energy supply system losses [3]. Over the past few decades, there has been extensive research on optimization methods for determining the location and capacity of renewable energy sources to minimize power loss, reduce voltage fluctuations, and enhance supply system reliability [2, 4-7].

Numerous studies have concentrated on optimization techniques to determine the placement and size of renewable energy systems (RES) to minimize power loss, decrease voltage fluctuations, and improve the reliability of the electric power supply. Various algorithms and solutions have been proposed to address this. For example, Rosa et al. [8] presented a novel approach that employs sensitivity analysis and optimal power flow techniques, utilizing computational tools and global search techniques with low computational time to allocate energy efficiently. In a separate study, researchers applied the Particle Swarm Optimization (PSO) algorithm to identify the optimal location and capacity of RES, aiming to reduce harmonic distortion, power loss, and overall system costs [9]. Furthermore, Khan et al. [10] used a numerical optimization algorithm to determine renewable energy systems' optimal placement and size, focusing on minimizing power loss and voltage deviations. Their study also introduced a voltage stability indicator and utilized numerical optimization in conjunction with phase synchronization data obtained from Phasor Measurement Units (PMUs).

This paper also introduces a method for determining the location and capacity of solar power systems integrated into distribution networks. The purpose is to minimize power loss, decrease voltage fluctuations, and maximize profit. The proposed method combines the Hill Climbing search principle and the Newton method to identify the optimal location for solar power systems near load centers and calculate the corresponding optimal power values with the fastest convergence speed. These values are determined as the combination that minimizes the objective function. Implementing this method in Matlab was tested on 33-bus and 69-bus test systems.

2. PHOTOVOLTAIC (PV) POWER SYSTEM INTEGRATION STRUCTURE

The grid-connected solar power source can be divided into five functional parts. These include a system of solar panels that converts solar radiation energy into electricity and a battery system that stores the generated electrical energy and supplies electrical energy to the grid. There's also a charging system to control the transfer of electrical energy generated from solar panels to the battery storage system, preventing back-supplied current from the battery storage system or the grid from returning to the solar cells. Additionally, an inverter converts the direct current stored in the battery into an alternating current with frequency and amplitude that is compatible with the consumer power grid. Finally, a transformer can make the power source compatible with the distribution grid. Depending on the scale and cost requirements, battery storage systems and charging systems can be used, and transformers may be needed specifically for large-capacity solar power plants or can be integrated into existing distribution transformers. The structural diagram of integrating the solar power system into the power distribution network is illustrated in Figure 1.

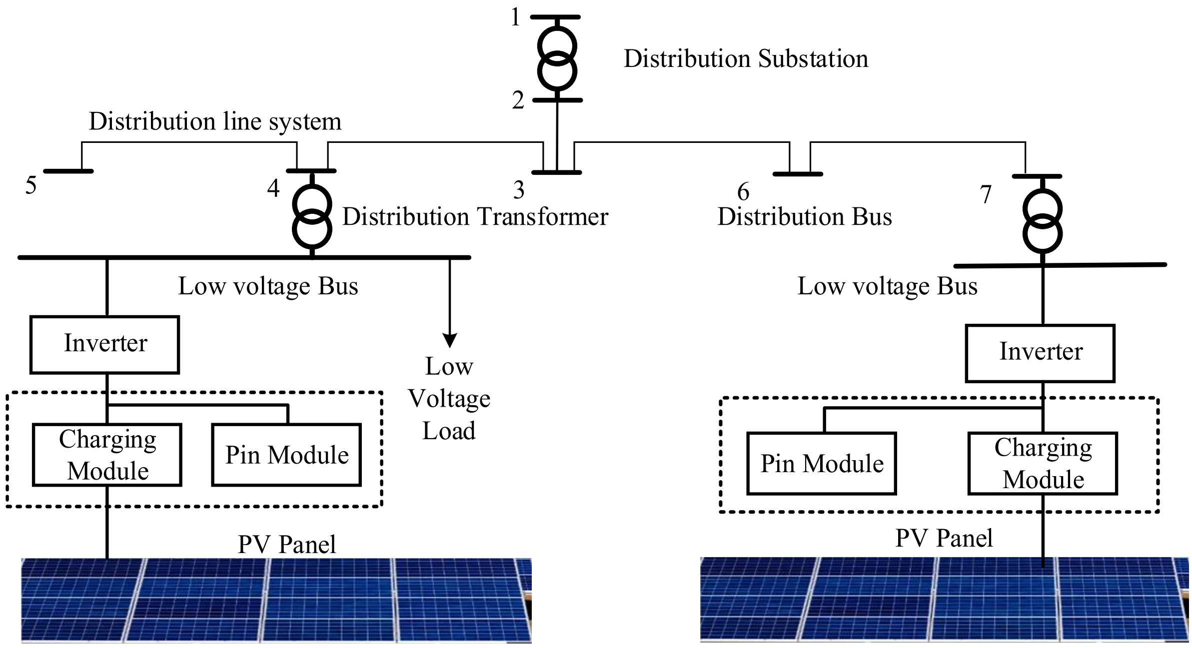

Figure 1. Structure diagram of grid-connected PV power system.

3. PROPOSED OPTIMIZATION SOLUTION

3.1. System modeling

The power distribution network system comprises distribution substations, transformers, medium voltage lines, and other equipment. Its primary function is to transmit electrical power from the source to end-users. These distribution lines are characterized by parameters such as resistance (r_{ik}), reactance (x_{ik}), total resistance (z_{ik}), and total conductivity (y_{ik}).

The distribution transformers serve as distribution buses that supply power to consumer loads. Each bus is defined by specific parameters, including voltage (V_i), phase angle (θ_i), active power (P_i), and reactive power (Q_i).

The voltage at the bus "i" can be characterized by its magnitude and phase angle:

$$\dot{U}_i = V_i\cos(\theta_i) + jV_i\sin(\theta_i) = V_i e^{j\theta_i} \tag{1}$$

The current at the buses is computed following the node voltages:

$$\dot{I}_i = \sum_{k\neq i}\left[y_{ik}\left(\dot{U}_i - \dot{U}_k\right)\right] = y_{ii}\dot{U}_i + \sum_{k\neq i} y_{ik}\dot{U}_k \tag{2}$$

With y_{ii} representing the sum of the conductances of the branches connected to bus i, and y_{ik} representing the total conductivity of the line connecting bus i to bus k.

The general equation describes the electrical circuit in matrix form as expression (3):

$$\begin{bmatrix}\dot{I}_1\\ \dot{I}_2\\ \vdots\\ \dot{I}_n\end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1nh}\\ y_{21} & y_{22} & \cdots & y_{2nh}\\ \vdots & \vdots & \vdots & \vdots\\ y_{n1} & y_{n2} & \cdots & y_{nnh}\end{bmatrix}\begin{bmatrix}\dot{U}_1\\ \dot{U}_2\\ \vdots\\ \dot{U}_n\end{bmatrix} \tag{3}$$

The power at the buses is described according to the relationship between node voltage and line parameters as follows:

$$\begin{aligned} S_i &= P_i + jQ_i = \dot{U}_i\tilde{I}_i = \dot{U}_i\sum_k \tilde{y}_{ik}\tilde{U}_k\\ &= \tilde{y}_{ii}\dot{U}_i\tilde{U}_i + \sum_{k\neq i}\tilde{y}_{ik}\dot{U}_k\tilde{U}_k\\ &= \tilde{y}_{ii}V_i^2 + \sum_{k\neq i}\tilde{y}_{ik}V_iV_k e^{j(\theta_i-\theta_k)}\\ P_i &= g_{ii}V_i^2 + \sum_{k\# i}V_iV_k[g_{ik}\cos(\theta_i-\theta_k) + h_{ik}\sin(\theta_i-\theta_k)]\\ Q_i &= -h_{ii}V_i^2 + \sum_{k\# i}V_iV_k[g_{ik}\sin(\theta_i-\theta_k) - h_{ik}\cos(\theta_i-\theta_k)] \end{aligned} \tag{4}$$

with P_i - active power at bus i; Q_i - reactive power at bus i; g_{ik} - real component of branch conductance ik; h_{ik} - imaginary component of branch conductance ik.

The current on the branches connecting bus i to bus k is described by Ohm's law:

$$\dot{I}_{ik} = -\dot{I}_{ki} = y_{ik}(\dot{U}_i - \dot{U}_k) \tag{5}$$

The calculation of power loss on the line branches is derived from the following formula:

$$\begin{aligned} Ploss_{ik} &= I_{ik}^2 r_{ik}\\ Qloss_{ik} &= I_{ik}^2 x_{ik} \end{aligned} \tag{6}$$

Where r_{ik} is the line resistance from bus i to bus k; x_{ik} is the line reactance connecting bus i to bus k.

The power distribution system model consists of a set of equations from (1) to (6). When solar energy penetrates the system, it directly impacts the power components of the buses, causing a redistribution of energy within the system. This redistribution then leads to changes in voltage and current throughout the system and changes in overall system losses.

3.2. Objective function

In this study, we are focused on determining the optimal location and capacity of the solar power system. Our objective function, precisely defined in expression (7), aims to strike a balance between reducing transmission losses and minimizing voltage fluctuations.

$$CF = m\text{in}(k_1.\frac{P_{loss}}{P_{total}} + k_2.VolDeviSum) \tag{7}$$

Where P_{loss} represents the aggregate power dissipation across the distribution line system, while P_{total} signifies the total active power of the entire system load. The relative ratio P_{loss}/P_{total} is employed to standardize the value reference system to align with the second power quality objective, known as *VolDeviSum*.

The term *VolDeviSum* refers to the cumulative value derived from squaring the voltage fluctuations of the buses expressed in per unit (pu).

$$VolDeviSum = \sum_{i=1}^{n_{bus}} (V_i - 1)^2) \tag{8}$$

The parameters k_1 and k_2 denote weighting coefficients that account for the equilibrium or bias between the objective of minimizing power loss and reducing voltage fluctuations. During this analysis, the research team adopted the values k_1=2 and k_2=1 for these coefficients.

The objective function is established with the following critical constraints:

The area, terrain, and geographical conditions delimit the permissible peak power in each deployment area:

$$P_{pv}(i) \le P_{cp}(i) \tag{9}$$

The current transmitted on distribution line branches must fall within the allowable rated limits:

$$I_{ik} \le I_{ik\_cp} \tag{10}$$

The voltage on the distribution buses must adhere to the standard limits:

$$0.95 \le V_i(pu) \le 1.05 \tag{11}$$

After achieving the technical objective, consideration can be given to the economic objective, which involves evaluating profits associated with the aforementioned technical solutions. Profit value is assessed over 10 years based on the storage battery life cycle estimates. The profit value is calculated by formula (12):

$$LNh(k) = (P_{pv}(k) * t_{tb} * \eta_{ht} + (P_{loss0} - P_{loss}(k)) * t_{lvtb}) * n_d * n_y * price - \sum_{i=1}^{n_{spv}} P_{pv}(i) * pri(i) \tag{12}$$

Where $P_{pv}(k)$ represents the total capacity of the entire solar power system under option *k*.

P_{loss0} is the total loss on the distribution system in the absence of the deployed solar power system, and $P_{loss}(k)$ is the total loss on the distribution system when the solar power system is deployed according to option *k*.

t_{tb} denotes the effective solar energy production time in a day, averaged over days in a year, and t_{lvtb} represents the average system working time in a day.

η_{tb} signifies the efficiency of the entire solar power conversion system.

n_d, n_y denote the number of days and years used for profit calculation. In this study, the number of years $n_y = 10$.

price refers to the cost of one kilowatt-hour (kWh) of electricity.

pri(i) represents the cost of deploying a solar power system per kilowatt-peak (KWp).

$P_{pv}(i)$ signifies the capacity of the *ith* solar power system in option *k*.

3.3. Optimization algorithm

To undertake the implementation of the objective function delineated in expression (7) and the condition constraints specified in expressions (8) to (11), the present study introduces an algorithm grounded in the Hill Climbing method to ascertain optimal locations for the deployment of solar power systems within the power grid, with a specific focus on identifying peaks corresponding to buses in proximity to the load center. The prioritization of peak search is structured, commencing with buses exhibiting the highest load values and progressing towards those with diminished loads. For diminutive electrical network systems encompassing a limited number of buses, a comprehensive assessment of the objective function value across all vertices proves conducive to achieving a globally optimized solution. Conversely, within extensive and exceedingly large power network systems, careful consideration of all peaks imposes a substantial computational burden, prompting the necessity to selectively narrow down the scope to approximately 1/10 to 1/2 of the total number of peaks, ensuring the algorithm's ability to discern the premier peak.

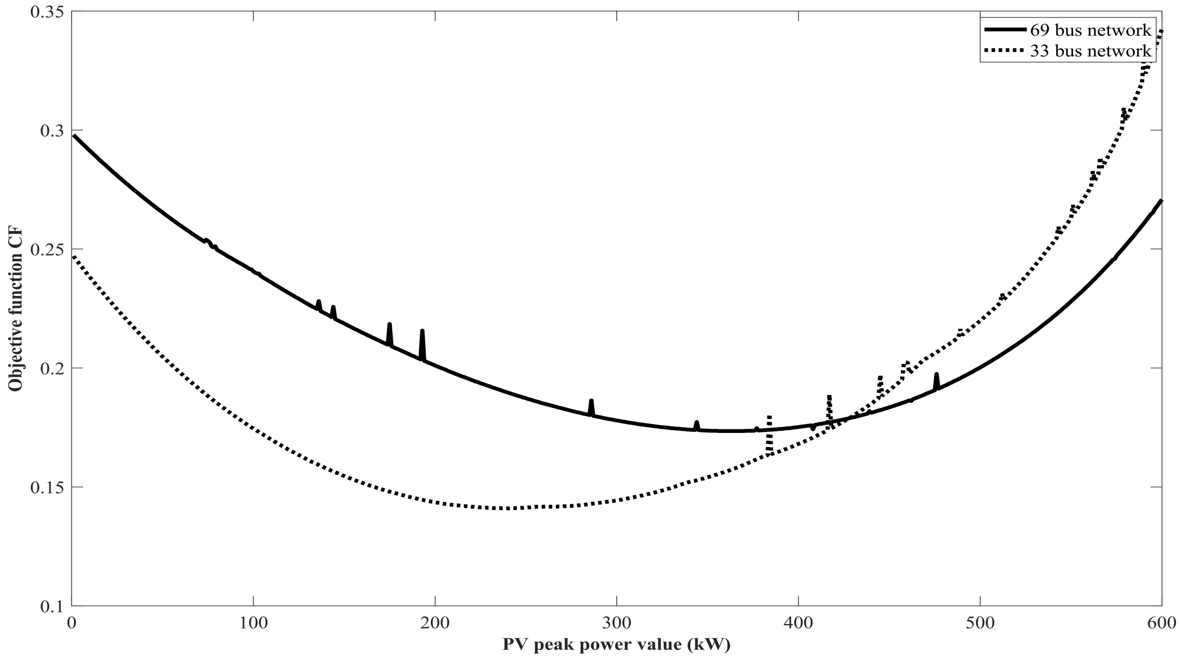

Figure 2. Relationship of objective function CF with PV peak power value.

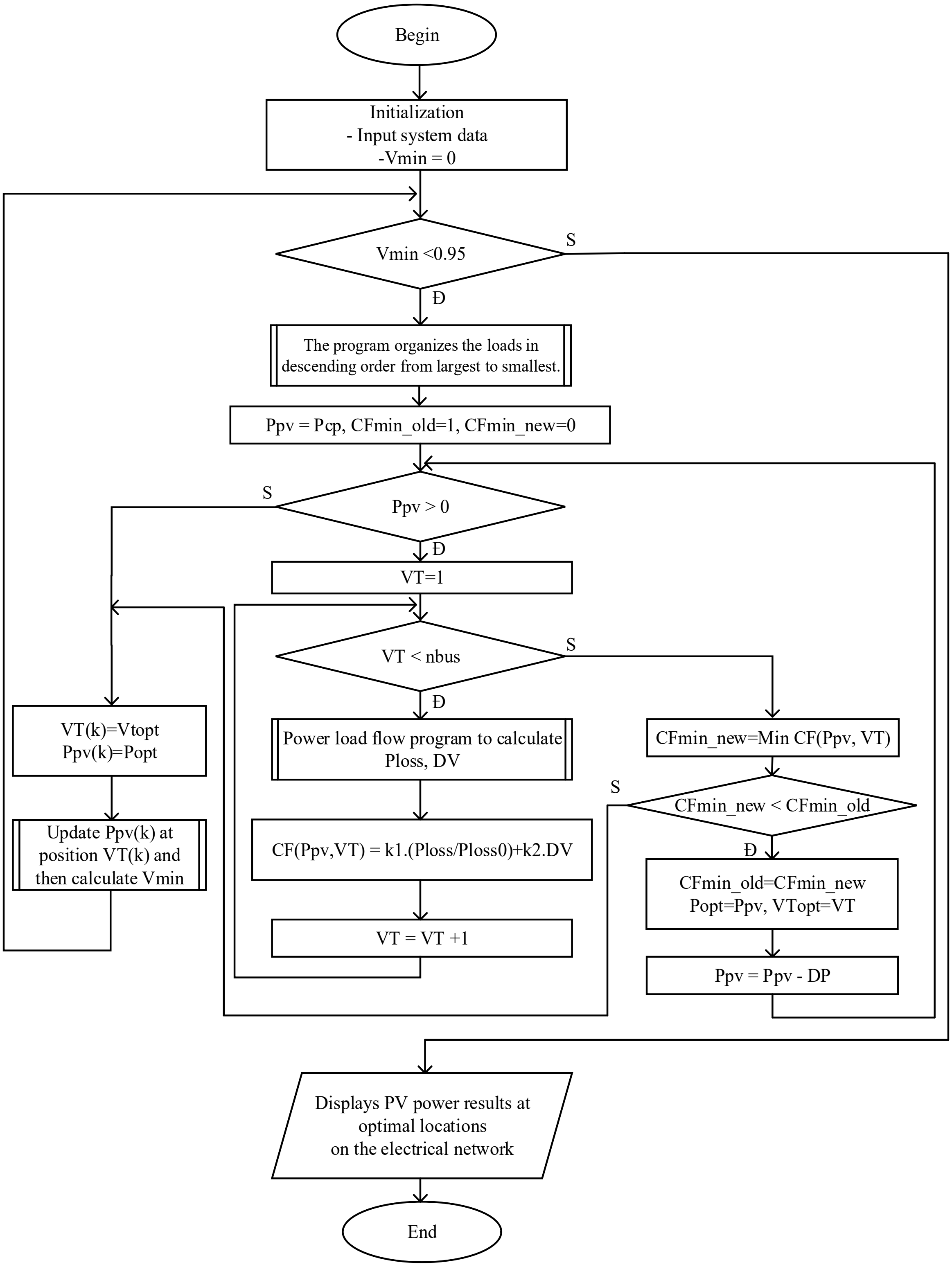

Figure 3. Flow chart of the proposed solution algorithm.

Additionally, a critical parameter pertains to the optimal capacity value of the renewable power system. Leveraging simulation software tools to ascertain the relationship between the objective function value articulated in expression (7) and the power value of RES for both 33-

bus and 69-bus IEEE systems, the study yields illustrative outcomes evident in Figure 2. Manifesting a quadratic nature, this relationship assumes a convex function form. Consequently, the determination of the power value *Ppv* to minimize the CF value function is conducted through the application of the Newton method, deploying the sequential steps outlined in the prescribed formula (13):

$$P_{pv}(i+1) = P_{pv}(i) - DP = P_{pv}(i) - \frac{CF(i)}{CF'(i)} \tag{13}$$

In selecting P_{pv} *(0)*, the allowable peak power (P_{cp}) in regions where renewable energy systems are deployed is considered. The flow chart depicted in Figure 3 presents the algorithm's detailed steps.

4. SIMULATION RESULTS

The proposed solution was tested using the 33-bus medium voltage power network model (IEEE 33 bus benchmark test system) and the 69-bus radial distribution system. Data about the load, one-line diagrams, and line information for the systems are duly referenced in [11, 12].

The objective function value, derived from the construction algorithm, was analyzed as the peak power value of the integrated solar energy system within the power network at each location. Analysis of the survey results revealed a near-quadratic relationship between the objective function value and the power rating. This regular relationship facilitates the identification of regions with extreme values. Although the alteration of coefficients *k1* and *k2* does not modify the form of the value function, it does induce a shift in the minimum value of the function consequent to changes in solar energy source capacity influenced by coefficients *k1* and *k2*. Figure 4 presents the survey result of the value function for the 33-bus test system, elucidating that the optimal penetration power value resides within the 1400 to 2000 kW solar power system capacity range. Given the assumed permissible power value of 3000 kW, the optimal penetration power value can be ascertained after a few calculated steps according to expression (13).

Figure 5 shows the objective function value chart when deploying a solar power system with different power ratings at the buses in a 33-bus system. The smaller the objective function value, the higher the efficiency achieved, and it often tends to be distributed in load-focus areas. As illustrated in Figure 5, when arranging only one solar power system with a capacity of 1000 kW, the priority area for selecting the solar power system will be at bus locations from 10 to 18 and 26 to 33. This characteristic can be used to demonstrate that applying the Hill Climbing principle can completely find the optimal location to penetrate the solar energy system. If the systems are small in scale, the search process can be performed on all locations to find the most optimal location. For very large-scale systems, global searching can take a lot of effort and computational time; then, the number of search locations can be reduced to about 1/3 to 1/2 the size of the system. It is still possible to find the most optimal location.

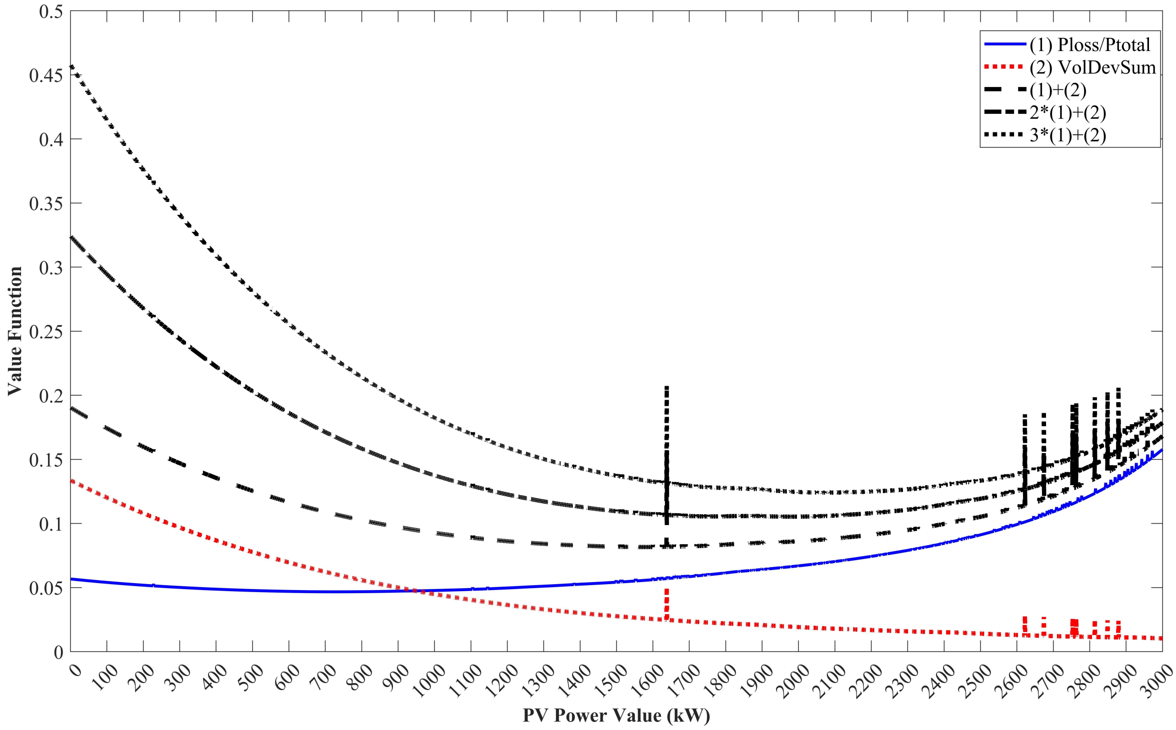

Figure 4. Variation of the objective function according to the peak power value.

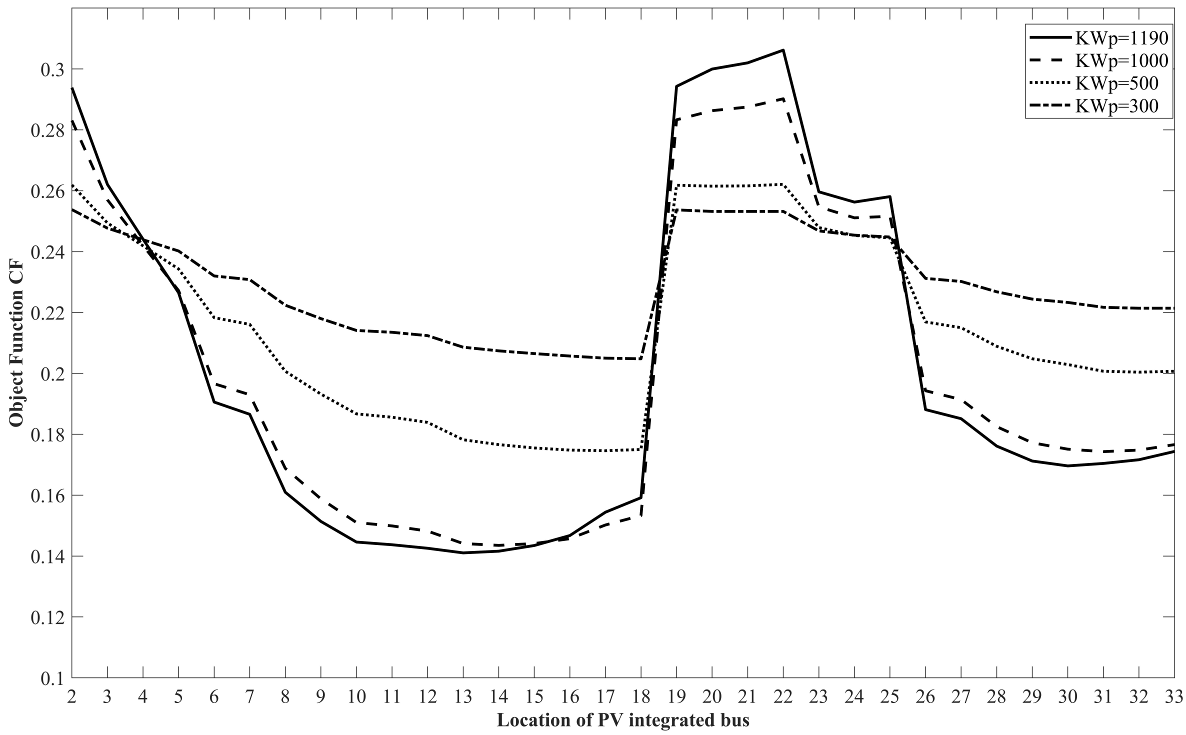

Figure 5. The objective function value (CF) for the PV system at the buses.

Table 1. Simulation results on 33 bus and 69 bus systems.

PV Power Restriction	IEEE 33 bus system			IEEE 69 bus system		
	PV Locations	PV power (kW)	Power Loss (kW)	PV Locations	PV power (kW)	Power Loss (kW)
KWp<300	17	245	93.0636	63	295	153.2639
	15	245		64	115	
	32	245		60	295	
	12	245		22	295	
	30	245		23	95	
	31	205		16	285	
				12	215	
				68	250	
KWp<500	16	495	95.031	63	495	129.9502
	31	495		60	495	
	10	495		22	495	
				64	115	
				13	280	
KWp<1000	13	995	91.5422	60	995	135.0856
	30	745		22	520	
				63	345	
KWp<1500	12	1190	93.4992	60	1305	142.5228
	31	625		22	480	

Table 1 presents the results of implementing the proposed algorithm when the solar power system peak power is limited to different norms implemented on the 33-bus and 69-bus systems. With the IEEE 33-bus system, considering the deployment capacity limit of 300 kW, it is necessary to deploy the solar power system in at least 6 areas. The optimal locations are near buses No. 12, 15, 17, 30, 31, and 32. The corresponding capacity is shown in the third column, in which station location 31 needs to deploy 205 kW, while the remaining five locations all deploy 245 kW. As for the IEEE 69-bus system, it needs to be deployed in 8 areas, specifically as illustrated in the data in table 1.

Figure 6 depicts the estimated profits associated with implementing a solar system under varying power rating limits. The discernible pattern of increased profitability corresponding to higher power rating limits substantiates the recommendation to maximize the utilization of the solar energy system within the permissible range.

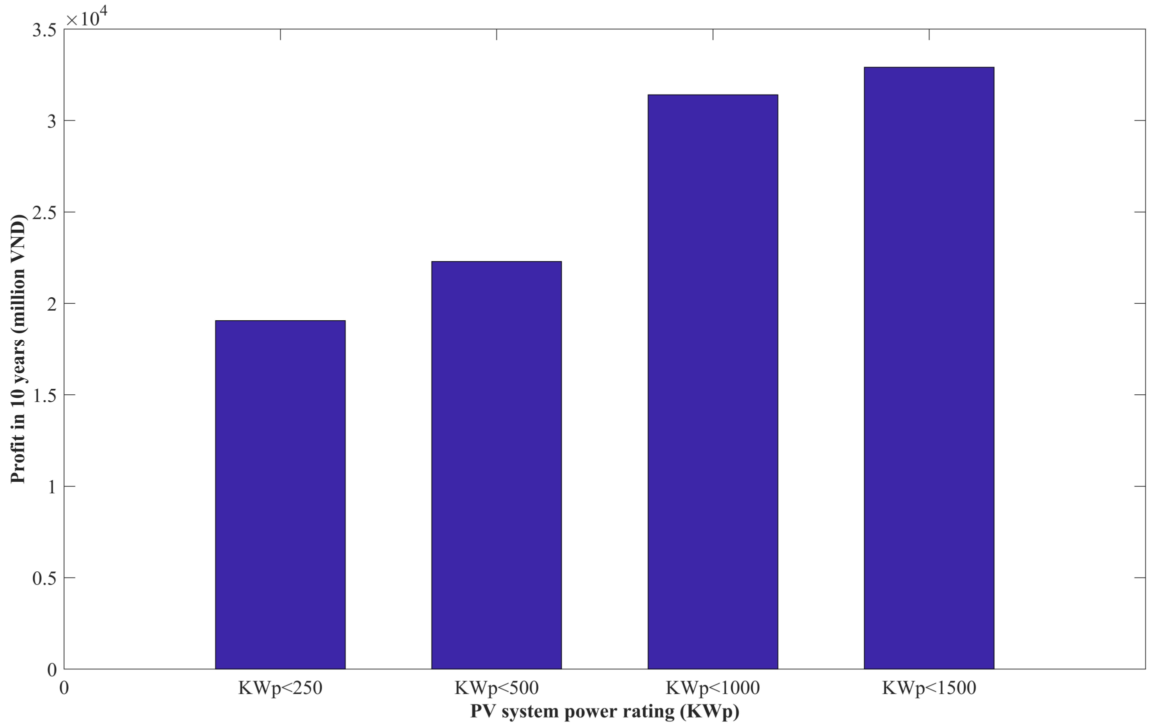

Figure 6. Estimated profit when implementing options according to solar power system capacity limits.

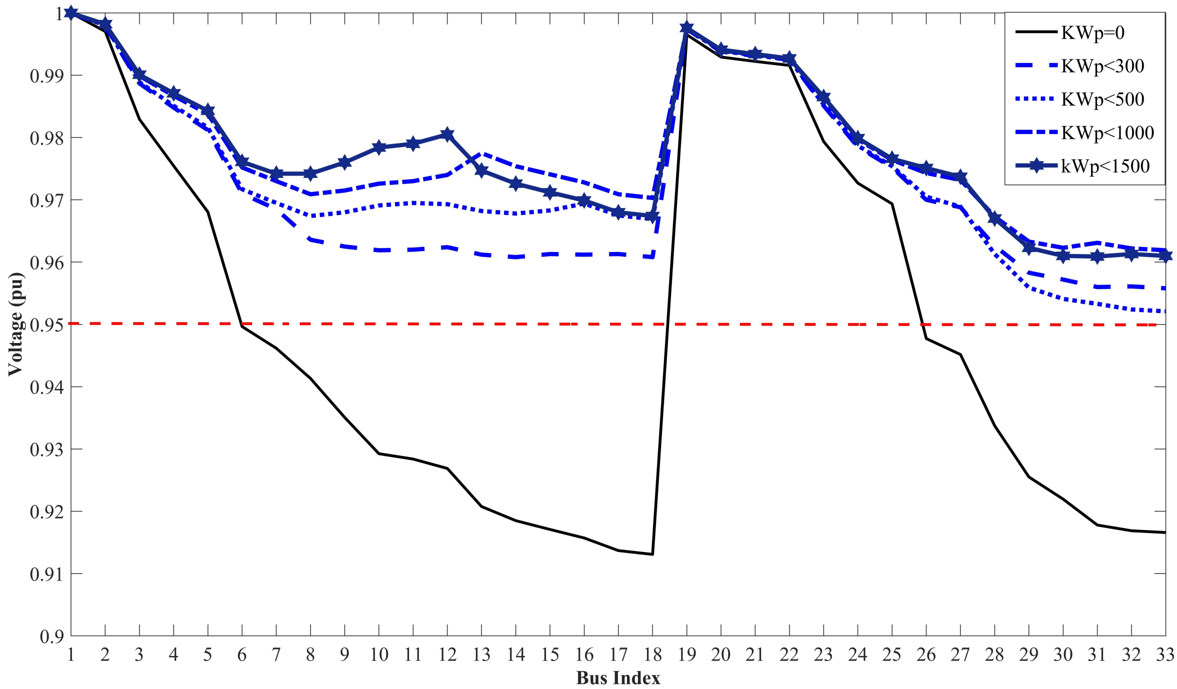

Figure 7. Voltages on the buses in the cases before and after PV system integration.

Figure 7 depicts the voltage levels on the respective buses before and after the implementation of the solar power system in the 33-bus power network. Before implementation (the line KWp=0), the lowest voltage recorded is 0.912 (pu) at bus number

18. Following the solar power system's deployment, the buses' voltage is consistently above 0.95 (pu), meeting the conditions set by the algorithm. Additionally, it is observed that as the power rating limit increases, the solutions implemented not only comply with the constraints but also demonstrate enhanced efficiency.

The presented data depicts the results of the proposed methodology on two test systems comprising 33 buses and 69 buses. The outcomes exhibit significantly enhanced voltage characteristics and substantial reduction in total power loss. These findings underscore the potential viability of the proposed method for deployment in the planning phase of renewable energy systems within actual power networks.

5. CONCLUSION

The article has presented a methodology for determining renewable energy systems' optimal siting and capacity within the medium voltage power network. This methodology utilizes the Hill Climbing principle to narrow down potential locations effectively and applies the Newton algorithm to calculate the power value, thus minimizing the objective function efficiently. The effectiveness of this approach was demonstrated through testing on two systems comprising 33 and 69 buses. The results indicated a significant reduction in total distribution system losses and voltage fluctuations by optimizing the siting and power rating of renewable energy systems integrated into the distribution network.

REFERENCES

[1]. Dongyang Zhang, Yumei Guo, Farhad Taghizadeh-Hesary, Green finance and energy transition to achieve net-zero emission target, Energy Economics, 126 (2023) 106936. https://doi.org/10.1016/j.eneco.2023.106936

[2]. Zeineb Abdmouleh, Adel Gastli, Lazhar Ben-Brahim, Mohamed Haouari, Nasser Ahmed Al-Emadi, Review of optimization techniques applied for the integration of distributed generation from renewable energy sources, Renewable Energy, 113 (2017) 266-280. https://doi.org/10.1016/j.renene.2017.05.087

[3]. Karim L. Anaya, Michael G. Pollitt, Integrating distributed generation: Regulation and trends in three leading countries, Energy Policy, 85 (2015) 475-486. https://doi.org/10.1016/j.enpol.2015.04.017

[4]. U. Sultana, Azhar B. Khairuddin, M.M. Aman, A.S. Mokhtar, N. Zareen, A review of optimum DG placement based on minimization of power losses and voltage stability enhancement of distribution system, Renewable and Sustainable Energy Reviews, 63 (2016) 363-378. https://doi.org/10.1016/j.renene.2019.09.117

[5]. Hamidreza Sadeghian, Zhifang Wang, A novel impact-assessment framework for distributed PV installations in low-voltage secondary networks, Renewable Energy, 147 (2020) 2179-2194. https://doi.org/10.1016/j.renene.2019.09.117

[6]. Omar A. Al-Shahri, Firas B. Ismail, M.A. Hannan, M.S. Hossain Lipu, Ali Q. Al-Shetwi, R.A. Begum, Nizar F.O. Al-Muhsen, Ebrahim Soujeri, Solar photovoltaic energy optimization methods, challenges and issues: A comprehensive review, Journal of Cleaner Production, 284 (2021) 125465. https://doi.org/10.1016/j.jclepro.2020.125465

[7]. Mohammed Hamouda Ali, Salah Kamel, Mohamed H. Hassan, Marcos Tostado-Véliz, Hossam M. Zawbaa, An improved wild horse optimization algorithm for reliability based

optimal DG planning of radial distribution networks, Energy Reports, 8 (2022) 582-604. https://doi.org/10.1016/j.egyr.2021.12.023

[8]. William M. da Rosa, Julio C. Teixeira, Edmarcio A. Belati, New Method for Optimal Allocation of Distribution Generation Aimed at Active Losses Reduction, Renewable Energy, 123 (2018) 334-341. https://doi.org/10.1016/j.renene.2018.02.065

[9]. Hamid HassanzadehFard, Alireza Jalilian, Optimal sizing and location of renewable energy based DG units in distribution systems considering load growth, International Journal of Electrical Power & Energy Systems, 101 (2018) 356-370. https://doi.org/10.1016/j.ijepes.2018.03.038

[10]. Mohd Tauseef Khan, Pushpendra Singh, Anurag Chauhan, Rajesh Arya, Aanchal Verma, L.S. Titare, S.C. Choube, Optimal Placement of multiple Distributed Generators using a Novel Voltage Stability Indicator employing Arithmetic Optimization Algorithm, Computers and Electrical Engineering, 110 (2023) 108853. https://doi.org/10.1016/j.compeleceng.2023.108853

[11]. Sarineh Hacopian Dolatabadi, Maedeh Ghorbanian, Pierluigi Siano, An Enhanced IEEE 33 Bus Benchmark Test System for Distribution System Studies, IEEE Transactions on Power Systems, 36 (2021) 2565 - 2572. https://doi.org/10.1109/TPWRS.2020.3038030

[12]. A. F Abdul Kadir, Azah Mohamed, Hussain Shareef, M.Z.C. Wanik, Optimal placement and sizing of distributed generations in distribution systems for minimizing losses and THD v using evolutionary programming, Turkish Journal of Electrical Engineering and Computer Sciences, 21 (2013) 2269-2283. http://dx.doi.org/10.3906/elk-1205-35