International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 5 Issue 4, April - 2021, Pages: 236-240

Optimal Planning of Photovoltaic based DG Units in Distribution Network Considering Uncertainties

Hasanov Mansur

Faculty of Power engineering and Radio electronics
Jizzakh Polytechnic Institute
Jizzakh city, Uzbekistan
mansur_hasanov@mail.ru

Abstract— *Global environmental problems associated with traditional energy generation have led to a rapid increase in the use of renewable energy sources (RES) in power systems. The integration of renewable energy technologies is commercially available nowadays, and the most common of such RES technology is photovoltaic (PV). This paper proposes an application of Differential Evolution (DE) algorithm for determining the optimal allocation of PV based distributed generation (DG) units in the distribution network (DN) with the aim of minimizing the total power and energy losses.*

Keywords— uncertainties; photovoltaic array; differential evolution algorithm; distribution network

1. INTRODUCTION

In the last few years, considerable attention has been paid to the usage of RES (such as PV, wind, etc.) to minimize power losses due to global environmental problems associated with traditional generation. Many countries have been introduced or are proceeding towards the implementation of renewable energy policies like the Renewable Energy Portfolio Standard (RPS) [1]. Accepting an RPS is a production obligation of a certain percentage of the total electricity production from RES for a specific date. However, available PV energy is unstable and variable. However, high PV integration can lead to large power fluctuations, which may risk the provision of continuous power supply. In addition, the amount of PV energy that can be absorbed by the power system at a particular time may be significantly limited, since the available traditional units may not be able to respond to changes caused by PV units' fluctuations [1-3].

PV produces energy when exposed to sunlight, and several other components are needed to properly conduct, control, convert, distribute and store the energy produced by the array. In restructured power systems, the use of distributed generation energy resources, including photovoltaic (PV), fuel cells, small wind turbines, etc. The advantage of distributed generation energy resources includes reducing power losses, improving voltage profile (VP), and increasing network reliability. To achieve the advantages of DG units, the choice of the optimal location and size becomes a major problem [3-5].

2. PROBLEM FORMULATION

Objective function

The objective of this article is to minimization the real power loss and improve the DN voltage [6-7].

Real power loss

The first term of the objective function is the real power loss, which is determined by equation (1)

$$P_{LOSS} = \sum_{j=1}^{n_f} \sum_{k=1}^{n_s} R_k \, |{I_k}^2| \tag{1}$$

Accordingly, minimizing the total active power losses in the DS leads to reduce the total active energy losses E_{loss} during 24 hrs as:

$$E_{loss} = \sum_{t=1}^{24} P_{loss}(t) \Delta t \tag{2}$$

where,

$I_k -$ Is the current passing through line *k*

n_f − Is the total number of branches

n_s − Total number of sections in the system

R_k −Resistance of the line section between buses k and $k + 1$

Voltage Profile improvement

The second goal of this work is to improve the VP, which is represented by the VP index in equation (3) [10].

$$VP = \sum_{j=1}^{n_f} \sum_{k\in lb} |V_k - V_{ref,k}| \tag{3}$$

where,

lb − Collection of the load buses

$V_{ref,k}$ − Nominal voltage at load bus k.

V_k − Voltage amplitude at bus k.

3. PV AND LOAD MODELS

3.1. PV modeling

Power generation using PV unit is highly dependent on meteorological conditions, such as solar radiation, and ambient temperature. These conditions are directly related to geographic area. Hence, the effectiveness of the conditions of solar radiation in a certain area is usually analyzed at the initial stage for the effective use of PV panels. The standard deviation (SD) and mean of hourly solar radiation per day is calculated using collected historical data. Continuous PDF for an exact time interval is divided into stages, in each solar radiation within certain limits. The PV power generation is determined by all possible stages of probabilities in that hour. In this study, the step for solar radiation is 0.05 kW/m^2. The average value of each stage is used as output power calculation for this stage (i.e. if the first stage of solar irradiation, is between 0 kW/m^2 and 0.05 kW/m^2, the average value of this stage is 0.025 kW/m^2).

3.1.1. Solar radiation model

It is considered that the probabilistic nature of solar radiation follows the Beta PDF [8-9]. The Beta PDF of solar radiation 's' (kW/m^2) in the time interval 't' is defined as:

$$f_b(s^t) = \begin{cases} \dfrac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} s^{t(\alpha^t - 1)} (1 - s^t)^{(\beta^t - 1)}, & 0 \le s^t \le 1, \quad \alpha^t, \beta^t \ge 0 \\ 0, & otherwise \end{cases} \tag{4}$$

where, $f_b(s^t)$ is the Beta PDF of s^t; α^t and β^t are the shape rates of Beta PDF , Γ is depict Gamma function.

The shape rates can be found based on the mean (μ) and SD (σ) of radiation for a suitable time interval.

$$\beta^t = (1 - \mu^t)\left(\frac{\mu^t(1+\mu^t)}{\sigma^{t2}} - 1\right), \qquad \alpha^t = \frac{\mu^t * \beta^t}{1 - \mu^t}.$$

A) PV array power generation

The PV array hourly average power output corresponding to an exact time interval 't' (P^t_{PV}) is expressed as (5). A typical day for three years is generated in p.u., as shown in Fig 1.

$$P^t_{PV} = \sum_{g=1}^{n_s} P_{PV_o}(s^t_g)\, f_b(s^t_g) \tag{5}$$

International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 5 Issue 4, April - 2021, Pages: 236-240

where 'g' denotes a stage factor and n_s is the solar radiation discrete stage number. S^t_g is the g^{th} stage of solar radiation at t^{th} time interval.

Solar radiation and ambient temperature are the basic dominant factors that affect the PV array power output. The PV power generation with average solar radiation (s_{ag}) for the g^{th} stage is estimated as [8-9]:

$$P_{PV_o}(s_{ag}) = N_{PV\,\mathrm{mod}} * FF * V_g * I_g \tag{6}$$

where

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{OC} * I_{SC}};\ V_g = V_{OC} - K_v * T_{cg};\ I_g = s_{ag}\left[I_{SC} + K_i(T_C - 25)\right];\ T_{cg} = T_A + s_{ag}\left(\frac{N_{OT} - 20}{0.8}\right)$$

Here, N_{PVmod} is the PV modules total number; T_A(°C) is ambient temperature; V_{MPP} and I_{MPP} are maximum power tracing voltage (V) and current(A), respectively; V_{OC} and I_{SC} are voltage of open-circuit and current of short circuit, respectively; K_i and K_v are the current and voltage temperature coefficients (A/°C and V/°C), respectively; FF is the fill factor; T_{cg} is PV module temperature at g^{th} stage (°C).

3.2. Load model

The load demand for the system is modelled corresponding to the normalized daily 24- hours load curve with a peak of 1 pu, as shown in Fig. 1 [8]. The load factor (LF) can determine as the field beneath the load curve, the load curve in p.u. subdivide by the sum of time interval [8]

$$LF = \sum_{t=1}^{24} \frac{per.unit.\quad Demand(t)}{24} \tag{7}$$

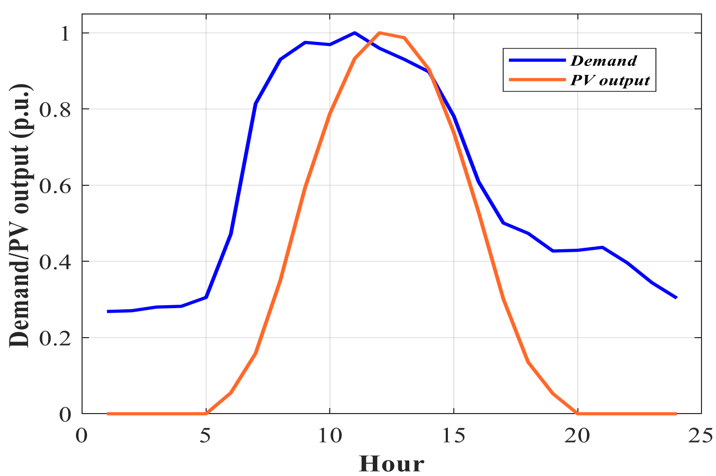

Fig 1. Normalized daily active load curve and PV output

The voltage-dependent load demand model, which includes variable load over time, can be calculated as [8-9]:

$$P_k(t) = P_{ok}(t) * V_k^{n_p}$$
$$Q_k(t) = Q_{ok}(t) * V_k^{n_q} \tag{8}$$

where, P_k and Q_k represent active and reactive power injected at node *k*. P_{ok} and Q_{ok} represent the active and reactive power loads injected at nodes *k*. V_k represents the voltage value at node *k*, and n_p and n_q represent active and reactive load demand voltage indexes, respectively [8-9], where n_p = 1.51 and n_q = 3.4.

International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 5 Issue 4, April - 2021, Pages: 236-240

4. DIFFERENTIAL EVOLUTION ALGORITHM (DEA)

Differential Evolution Algorithm (DEA) is a robust and versatile function optimizer that is easy to use and delivers results in a very short period [11]. It is a simple and extremely powerful method of evolutionary computation that solves real-life problems based on the principles of natural evolution. The optimization process is carried out using three main operations: mutation, crossover, and selection. Once in every generation, each vector of parameters of the current population becomes a target vector or a parent vector. For each target vector, the mutation operation creates a new parameter vector, called the mutant vector, by adding the weighted difference between two randomly selected vectors to a third (also randomly selected) vector. The crossover operation generates a new vector, a test vector, by mixing the parameters of the mutant vector with the parameters of the target vector. If the trial vector has a better fitness value than the target vector, then the trial vector replaces the target vector in the next generation. Thus, after each generation, a new modified set is created, and this continues until the iteration is completed or a globally optimal solution is obtained. The flow chart of DEA is shown in Fig.2.

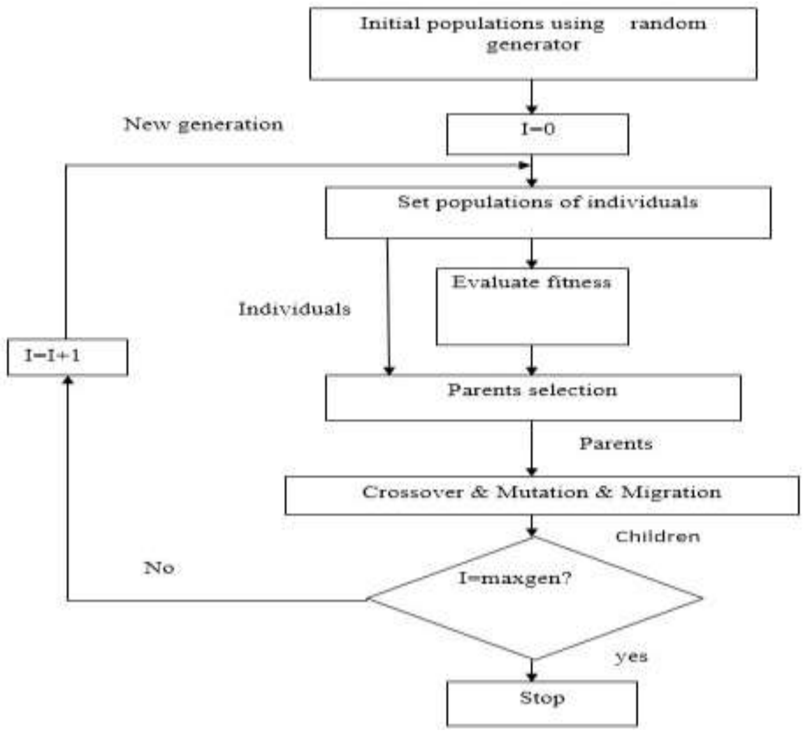

Fig. 2. Flow chart for DEA

5. SIMULATION AND RESULTS

Based on the proposed methodology, a program was written in MATLAB software. To evaluate the effectiveness of the proposed approach, the program was applied to test systems at nominal load. The test system is a standard 33-bus DN with a total load of 3.7 MW and 2.3 MVar as shown in Fig.3. The power flow is performed using S_{base} = 100MVA and V_{base} = 12.66 kV [12]. The power losses in the base case are 210.986 kW. The VP index is 0.90378 pu.

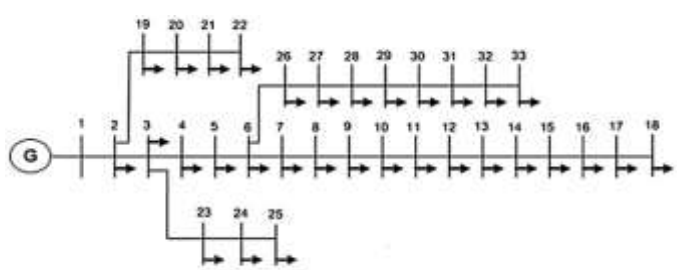

Fig.3. The standard 33-bus distribution system

In this paper, the power flow is analyzed using the reverse / forward sweep algorithm in the base case. Without PV array allocation and with optimal PV array allocation. The observed results are presented in Table 1 and Table 2. It can be seen from the results that the integration three PV based DG units improve DN performance.

Table 1: The observed results for 33-bus system

PV- location	PV- size/PF	Power loss	Voltage profile (minimum voltage at the bus)
13 30 24	801.71/1 1053.6/1 1091.3/1	72.790	0.96 @ bus 33

Table 2 Daily energy loss for 33-bus system

Scenario	Energy loss (kW h)	Loss reduction %
Base case	2044.796	-
With PV	1036.09	49

6. Conclusion

The proposed approach is used to reduce power losses, energy loss and improve VP in the distribution network. To test the effectiveness of the proposed approach was tested on a test system with a standard 33 bus system. For the 33-bus system, the loss reduction is 53% and energy loss reduction is 49%. In addition, the VP performance is improved over the base system.

References

[1] Khasanov, Mansur, et al. "Rider Optimization Algorithm for Optimal DG Allocation in Radial Distribution Network." *2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES)*. IEEE, 2020.

[2] Khasanov, Mansur, Salah Kamel, and Hussein Abdel-Mawgoud. "Minimizing Power Loss and Improving Voltage Stability in Distribution System Through Optimal Allocation of Distributed Generation Using Electrostatic Discharge Algorithm." *2019 21st International Middle East Power Systems Conference (MEPCON)*. IEEE, 2019.

[3] Khasanov, Mansur, et al. "Allocation of Photovoltaic and Wind Turbine Based DG Units Using Artificial Ecosystem-based Optimization." *2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*. IEEE, 2020.

[4] Khasanov, Mansur, et al. "Allocation of Distributed Generation in Radial Distribution Networks Using an Efficient Hybrid Optimization Algorithm." *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*. IEEE, 2019.

[5] Khasanov, Mansur, et al. "Combined Tree Growth Algorithm for Optimal Location and Size of Multiple DGs with Different Types in Distribution Systems." *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*. IEEE, 2019.

[6] Urinboy, Jalilov, and Mansur Hasanov. "Improvement Performance Of Radial Distribution System By Optimal Placement Of Photovoltaic Array." *International Journal of Engineering and Information Systems (IJEAIS)* 5.2 (2021): 157-159.

[7] Kamel, Salah, et al. "Radial Distribution System Reconfiguration for Real Power Losses reduction by Using Salp Swarm Optimization Algorithm." *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*. IEEE, 2019.

[8] KHASANOV, Mansur, et al. "Optimal planning DG and BES units in distribution system considering uncertainty of power generation and time-varying load." *Turkish Journal of Electrical Engineering & Computer Sciences* 29.2 (2021): 773-795.

[9] Abdel-Mawgoud, H., et al. "A strategy for PV and BESS allocation considering uncertainty based on a modified Henry gas solubility optimizer." *Electric Power Systems Research* 191 (2021): 106886.

[10] Abdel-Mawgoud, Hussein, et al. "Simultaneous Allocation of Multiple Distributed Generation Units in Distribution Networks Using Chaotic Grasshopper Optimization Algorithm." *2019 21st International Middle East Power Systems Conference (MEPCON)*. IEEE, 2019.

[11] Storn, Rainer, and Kenneth Price. "Differential evolution a simple evolution strategy for fast optimization." *Dr. Dobb's journal* 22.4 (1997): 18-24.

[12] Mashhour, M., M. A. Golkar, and SM Moghaddas Tafreshi. "Optimal sizing and siting of distributed generation in radial distribution network: Comparison of unidirectional and bidirectional power flow scenario." *2009 IEEE Bucharest PowerTech*. IEEE, 2009.