

Optimal Operation of Photo Voltaic (PV) units using Learning Automata Algorithm in Unbalanced Distribution Network

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Abstract: The electric power industry is pacing towards renewable and Distributed Energy Resources (DERs) because of the increasing environmental interests. The integration of Distributed Generation(DG) technologies has gained much interest in the past decade because of their capability to improve the voltage profile, reduce losses and improve the overall integrity and efficiency of the system. The Photo Voltaic (PV) source is becoming more popular since they are abundant and commonly available. The widespread use of the DG technologies demands efficient power flow studies to be carried out for distribution system. The benefits of DG integration can be achieved only with the optimal allocation of DG sources into the radial distribution network. The paper presents an algorithm based on the Reinforcement Learning (RL) to find out the optimal size of the PV units in an unbalanced distribution network. The proposed algorithm is validated and tested for the IEEE 13 bus and IEEE 37 bus distribution feeders..

Keywords: Forward Backward Sweep; Optimal DG Placement; Learning Automata.

1. INTRODUCTION

The thrive towards environmental friendly sources of energy has led most of the countries to adopt Distributed Generation (DG) sources to meet the growing demand for electricity. The improvement in voltage profile, reliability, reduction in losses, elimination of system upgrades are some of the benefits of DG integration [1]. The widespread use of DG in the distribution system poses various challenges to the power industry since they cause the transformation of the network into active [2]. The challenges can be technical, commercial and regulatory challenges [3], [4] . The benefits can be maximized and the Challenges can be minimized only by optimal placement of DG into the distribution network [5], [6]. The problem of optimal allocation of the DG units into the distribution network is otherwise referred as Optimal DG placement problem (ODGP). This involves the calculation of the most beneficial DG capacity as well as the best location where it is to be installed so that the efficiency of the overall power network is improved subjected to electrical operating constraints. ODGP problem has been an attracting research area since last decade and a variety of approaches were applied in order to deal with the ODGP problem.

The objective function considered in most of the studies was the minimization of the network losses. There is a significant variation in the method adopted for the optimal allocation of DG units. The methods can be broadly classified as analytical methods, numeric methods and the heuristic methods. The analytic methods involves the optimization by using the simple analytical expressions for Loss sensitivity factor, exact loss formula etc. for the optimizing the size and location of DG units. Because of the robustness and ability to handle complex data to find an optimal solution, heuristic algorithms are widely used for

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optimization of DG units. From the review of the previous works, most of the works involved optimization without considering the randomness of the DG sources and the load profile. The energy production from the DG units such as Photo Voltaic (PV) source and wind power plants bank on the fundamental energy values at the location of DG installation. These values are random in nature and limited prediction is possible. This results in the fact that the output power of the DG source is of uncertain nature. This requires the optimization to be run on a stochastic basis. The disadvantage of the heuristic optimization methods discussed earlier is their inability to handle stochastic data in practical system. Reinforcement learning (RL) is a learning method which involves learning by interactions with environment, mapping the situations to actions so as to maximize the reward and minimize the punishments. RL can handle the stochastic data and can be applied for multistage decision making situations without the need to formulate a precise mathematical model to start with. RL have been applied to many decision making situations in power system such as unit commitment, economic dispatch and automatic generation control. The application of RL for ODGP problem is yet need to be explored.

The objective of this paper is to optimally size the PV source for an unbalanced distribution system so as to minimize the total power losses for the network. This is done by analyzing the system parameters for voltage profile, line losses both active and passive in a radial distribution network of unbalanced nature by incorporating the PV source and the associated uncertainty by power flow analysis.

The paper is organized as follows. Section 2 gives a description of the proposed load flow algorithm with DG integration. Section 3 describes the Reinforcement learning approach used for the optimization of the PV source. Section 4 describes the case studies carried out for the proposed algorithm. The results for the test system and conclusions drawn from the study are given respectively in Section 5 and 6.

2. POWER FLOW ALGORITHM FOR DISTRIBUTION SYSTEM INCORPORATING DG UNITS

The steady state behavior of any power system is determined by using Power Flow Analysis. Because of the ill conditioned nature of the distribution system the conventional power flow algorithms can not be used. This necessitates the use of distinct algorithms for unbalanced radial distribution system. For solving the unbalanced distribution power flow so many algorithms were developed and quite a few were successful for DG inclusion [7]- [8]. The forward-backward sweep [9] method and the direct method proposed by Teng [10], [11] are the widely accepted method for unbalanced distribution system power flow .

The technique used here for solving the distribution feeder power flow is the modified Ladder Iterative technique given by Kersting. The two basic steps involved here are known as forward sweep and backward sweep. The forward sweep given in (1) is used to find the new nodal voltage and the new currents flowing through each branch is computed using backward sweep equations given by (2)

$$[VLN_{abc}]_m = [A] \cdot [VLN_{abc}]_n - [B] \cdot [I_{abc}]_n \quad (1)$$

$$[I_{abc}]_m = [c] \cdot [VLN_{abc}]_n + [d] \cdot [I_{abc}]_n \quad (2)$$

where $[VLN_{abc}]_m$; $[VLN_{abc}]_n$ used to denote the line to neutral voltage of nodes m and n respectively and $[I_{abc}]_m$; $[I_{abc}]_n$ symbolizes the line currents of nodes m and n respectively. The matrices A;B; c; d are generalized and constant matrices.

The initial step in solving the power flow involves the computation of no load voltages by assuming nominal voltage at the source node and initializing the currents of all the nodes in (1) as equal to zero. With this computed voltage the currents at the end nodes is computed. This is done from all the end nodes

through the junction node to the source node using current summation method. With this current the voltage at the source node is computed and the same is checked for acceptable limits. The resulting currents are used to compute voltage starting at the source node to all the end nodes using forward sweep. This is repeated till convergence is achieved.

2.1 Power flow solution incorporating DG sources

Depending on method of interconnection the size DG units can be modeled as PQ nodes or PV nodes for distribution power flow. When they are modeled as PQ nodes would not cause any challenge for distribution power flow because they can be considered as negative loads [8]. But it is necessary to make some changes in the power flow when DG units are considered as PV nodes. DG units modeled as PV nodes should be handled in a way described below in the power flow solution [12]. The DG units are considered as negative PQ nodes and the backward forward sweep is performed. When the power flow has converged solution the important steps to be followed are

1. The computation of the positive sequence voltage mismatch for each PV node is important since this forms the base for the calculation of generator terminal voltage. The tolerance of the mismatch vector is checked using (3)

$$\Delta V_1^k = |V_{1spec}^k| - |V_{1calc}^k| < \varepsilon \quad (3)$$

Here k is a PV node.

2. If the calculated voltage mismatch is less than the specified tolerance, then convergence is achieved for the PV node. Otherwise, in order to maintain the voltage profile at the PV node within the acceptable limit the reactive power injection required is to be found out. using positive sequence impedance sensitivity matrix.

$$\Delta I_Q^k = inv(Z_1^k) * \Delta V_1^k \quad (4)$$

Here the matrix Z_1^k is the positive sequence impedance square matrix of order where n denotesthe number of PV nodes. The sum of the positive sequence impedance of the line sections from each PV node to the substation node gives the diagonal elements . The sum of the series impedance of the line sections which are common to two PV nodes gives the off diagonal elements . The sign of ΔV_1^k determines the lagging and leading operation of DG . For positive ΔV_1^k , the DG unit is intended toproduce reactive power and for negative values of ΔV_1^k , the DG unit absorbs reactive power.

3. The reactive power production limit for DG is determined by the power factor. This is done by fixing the power factor between 0.8 and 1.

$$Q_{G,min}^k \leq Q_G^k \leq Q_{G,max}^k \quad (5)$$

If the reactive power computed for any of DG unit is not within the specified limits, the corresponding node is considered as PQ node. The corresponding current for reactive power injection is given by

$$\Delta I_{Q,limit}^k = \frac{Q_{limit}^k}{3 \cdot mag(V_1^k)} \quad (6)$$

4. The resulting currents are added to the load currents at the kth node to compute the total currents injected at the kth node

$$I_{Q,\Phi}^k = I_{\Phi}^k + \Delta I_{Q,\Phi}^k \quad \Phi = a, b, c \quad (7)$$

Using the resulting currents the load flow is run again until an acceptable value of voltage and voltage mismatch are obtained.

3. OPTIMIZING THE SIZE OF THE PV UNIT BY REINFORCEMENT LEARNING

3.1 Introduction

Reinforcement learning is a neurodynamic programming technique where the learning is carried out by continuous interactions with the environment. One of the key feature of the RL approach compared to the soft computing technique is that they are successful in handling the stochastic data existing in real world situations because of which they find applications in many decision making situations. The applications of Reinforcement Learning in power system are a few and need to be explored. The reinforcement learning have been successfully applied for solving the problems of economic dispatch, unit commitment and Automatic Generation Control (AGC). The Reinforcement learning is a new approach for ODGP problem. RL involves the mapping of certain situations to action by maximizing the rewards and minimizing the punishments. The reinforcement learning can be used to solve the multistage decision problems, by redefining the problems in terms of the state and actions. The action giving the maximum reward and the corresponding state will lead to the optimum solution. For finding out the optimum size of the PV units, the learning automata solution approach is used the ϵ -greedy algorithm is used to find out the optimal solution.

3.2 Problem Formulation

The Learning Automata system updates the performance index by taking up continuous actions. Each action $a_k \in A$ corresponds to a value of performance index whose value gets updated according to the actions. The values of the performance index associated with each set of actions are initialized as zeros. The best action is selected by the Learning algorithm using the exploration strategy and here ϵ -greedy algorithm is used as selection strategy. When any action $a_k \in A$ (the PV size) is applied from the action set, the LA algorithm gives the numerical value of the reward which is the total network loss corresponding to a_k , $Loss(a_k)$ where Loss is given by [13]

$$P_{loss} = \sum \sum A_{ij}(P_i P_j + Q_i Q_j) + B_{ij}(Q_i P_j + P_i Q_j) \quad (8)$$

Where

$$A_{ij} = \frac{R_{ij} \cos(\delta_i - \delta_j)}{V_i V_j}$$

$$B_{ij} = \frac{R_{ij} \sin(\delta_i - \delta_j)}{V_i V_j}$$

The performance index is updated using the value of reward or loss obtained using (9)

$$Q^{n+1}(a_k) = Q^n(a_k) + \alpha [Loss(a_k) - Q^n(a_k)] \quad (9)$$

Here α is the learning parameter whose value is fixed as 0.5 by trial and error method. The performance index is updated by changing the actions selected for sufficient number of times so that the changes in the value of performance index becomes negligibly small and the action corresponding to the optimum performance index is regarded as the best action with highest probability. After the learning system converges, the optimum size of the PV unit is found using (10)

$$a^* = \underset{a_k \in A}{\operatorname{argmin}} Q(a_k) \quad (10)$$

4. RESULTS AND DISCUSSIONS

4.1 IEEE 13 bus and 37 bus test system without and with the incorporation of DG Unit

The distribution power flow study was validated using the standard IEEE 13 bus test feeder and IEEE 37-Bus test feeder. The voltage magnitudes and the angles obtained are found to be comparable with the results obtained from the simulation package OpenDSS. The DG units were incorporated for the IEEE 13 bus distribution feeder at node 680. The DG units were modeled as PQ nodes as well as PV nodes. For PQ modeling, the DG units are included by considering negative loads. If DG units were incorporated as PQ nodes, there is a slight improvement in the voltage profile and when they are modeled as PV nodes, it can be seen that the voltage profile is further improved. The algorithm was validated for the IEEE 37 bus test system and the results obtained are found to be satisfactory.

4.2 Impact of modeling on the total losses

The real power losses for the three cases (without DG unit, Addition of DG unit as PQ node and Addition of DG unit as PV node is shown in Fig. 1. The losses are represented as percentage of the total power output. It can be seen that there is a substantial reduction in the losses from case 1 to case 3. While considering DG units as PV node, losses are again minimized due to the improvement in the voltage profile.

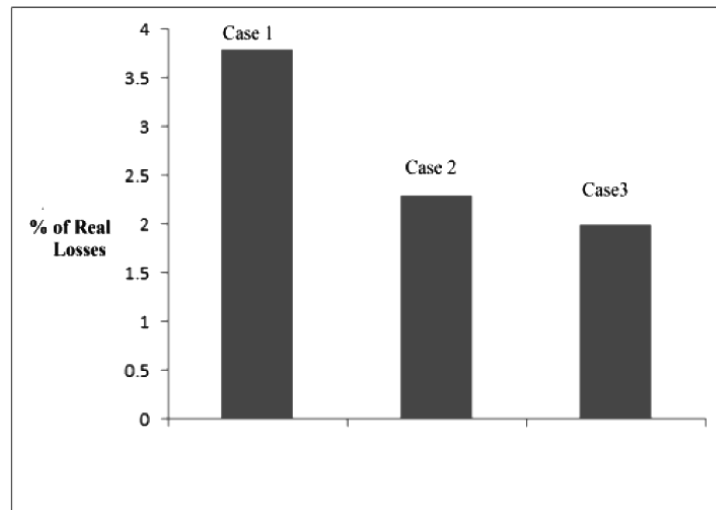


Figure 1: Comparison of Real Power Losses

4.3 Optimizing the size of the DG units using Learning Automata Algorithm

The learning automata algorithm is used for optimizing the size of the PV units in the IEEE 13 bus test feeder and the 37 bus test feeder. In the case of the IEEE 13-bus test feeder, the PV unit is installed at node 680 of the distribution feeder and in the case of the IEEE 37-bus test feeder, the PV unit is installed at node of the distribution feeder. The execution took only 255.5 seconds in the case of IEEE 13-bus distribution feeder and 337 seconds in the case of the IEEE 37 bus distribution feeder which proves the computational efficiency of the optimization method based on the learning automata algorithm. The optimum sizing of the PV units and the corresponding power loss for each phase is tabulated in Table 1.

Table 1
Power Loss and Optimum size of the PV units

	<i>IEEE 13 bus Feeder</i>		<i>IEEE 37 bus Feeder</i>	
	<i>Optimum PV size(kW)</i>	<i>Power Loss(kW)</i>	<i>Optimum PV size (kW)</i>	<i>Power Loss(kW)</i>
Phase A	900	29.73	550	24.55
Phase B	650	0.656	750	8.691
<i>Phase C</i>	<i>1250</i>	<i>2.543</i>	<i>800</i>	<i>21.98</i>

6. CONCLUSION

The paper focuses on the optimal allocation of the PV unit in an existing distribution network by making use of the robust Reinforcement Learning (RL) approach for optimization. The widespread use of DG sources demands efficient analysis to be carried out for the Distribution network. The analysis was carried out with the help of the power law algorithm. The Learning Automata algorithm is used to estimate the optimum size of the PV unit to be installed in the distribution feeder. IEEE 13-bus test feeder and the IEEE 37 Bus distribution feeder are used to validate the power flow algorithm without and with the incorporation of Photo Voltaic sources. The results indicate that the optimization technique is fast and robust for optimizing the size of the PV unit to be installed in the existing distribution network. This suggests a scheme for the utility to efficiently plan the integration of DG source before installing PV sources to the distribution network.

References

- [1] Pathomthat Chiradeja and R Ramakumar. An approach to quantify the technical benefits of distributed generation. *Energy Conversion, IEEE Transactions on*, 19(4):764-773, 2004.
- [2] JA Lopes, N Hatziargyriou, J Mutale, P Djapic, and N Jenkins. Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electric Power Systems Research*, 77(9):1189-1203, 2007.
- [3] Johan Driesen and Ronnie Belmans. Distributed generation: challenges and possible solutions. In Power Engineering Society General Meeting, 2006. IEEE, pages 8 pp. IEEE, 2006.
- [4] Philip P Barker and Robert W de Mello. Determining the impact of distributed generation on power systems. i. radial distribution systems. In Power Engineering Society Summer Meeting, 2000. IEEE, volume 3, pages 1645-1656. IEEE, 2000.
- [5] Zhaoyu Wang, Bokan Chen, Jianhui Wang, Jinho Kim, and Miroslav M Begovic. Robust optimization based optimal dg placement in microgrids. *Smart Grid, IEEE Transactions on*, 5(5):2173-2182, 2014.
- [6] Nguyen Cong Hien, Nadarajah Mithulananthan, and Ramesh C Bansal. Location and sizing of distributed generation units for loadability enhancement in primary feeder. *IEEE Systems Journal*, 7(4):797-806, 2013.
- [7] Sarika Khushalani, Jignesh M Solanki, and Noel N Schulz. Development of three-phase unbalanced power law using pv and pq models for distributed generation and study of the impact of dg models. *Power Systems, IEEE Transactions on*, 22(3):1019-1025, 2007.
- [8] SM Moghaddas-Tafreshi and Elahe Mashhour. Distributed generation modeling for power law studies and a three-phase unbalanced power law solution for radial distribution systems considering distributed generation. *Electric Power Systems Research*, 79(4):680-686, 2009.
- [9] WH Kersting. A method to teach the design and operation of a distribution system. *Power Apparatus and Systems, IEEE Transactions on*, (7):1945-1952, 1984.
- [10] Jen-Hao Teng and Chuo-Yean Chang. A novel and fast three-phase power law for unbalanced radial distribution systems. *Power Systems, IEEE Transactions on*, 17(4):1238-1244, 2002.

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- [11] Jen-Hao Teng. A direct approach for distribution system load flow solutions. *Power Delivery, IEEE Transactions on*, 18(3):882-887, 2003.
- [12] Maya, K. N., and E. A. Jasmin. "A generalised three phase power flow algorithm incorporating the uncertainty of Photo Voltaic (PV) source for unbalanced distribution network." *Advancements in Power and Energy (TAP Energy), 2015 International Conference on*. IEEE, 2015
- [13] Duong Quoc Hung and Nadarajah Mithulananthan. Multiple distributed generator placement in primary distribution networks for loss reduction. *Industrial Electronics, IEEE Transactions on*, 60(4):1700-1708, 2013.

