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# Optimal placement of DGs in a multi-feed radial distribution system using actor-critic learning algorithm

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**ABSTRACT**

Multi-feed radial distribution systems are used to reduce the losses in the system using reconfiguration techniques. Reconfiguration can reduce the losses in the system only to a certain extent. Introduction of distributed generators has vastly improved the performance of distribution systems. Distributed generators can be used for reduction of loss, the improvement of the voltage profile, and reliability enhancement. Distribution generators play a vital role in reducing the losses in the distribution system. Placement of distributed generators in a multi-feed system is a complex task to be solved using classical optimization methods. Classical optimization techniques may sometimes fail to provide a converged solution. Installation of distributed generators at suitable locations in a multi-feed system is found in this paper using the actor-critic learning algorithm. Actor-critic learning approach uses temporal difference error as a signal in making judgements regarding actions to be taken for future states in accordance with rewards that have been obtained by applying the present policy. The approach is applied to a standard 16-bus distribution system for reduction of system losses, and the results are discussed.



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## 1. INTRODUCTION

Distributed generation (DG) has been playing a vital role in the electric power system for the past few years [1]. It has led to several benefits like environmental protection in case of renewable DG, deferment of feeder upgradation under load growth, voltage profile enhancement, reduction in losses, and in reliability enhancement of the system [2]. An extensive research has been made till now for single DG placement, and relatively little work has been done in the case of multiple DG placement. DG placement using a fuzzy logic approach has been done in [3]. Previous study [4], the optimal placement of DGs in a microgrid has been performed. Probabilistic placement of DG has been performed in [5] considering uncertainties. DG planning using the enhanced search group algorithm is done in [6]. DG planning using a Monte Carlo simulation has been done in [7]. Distribution system planning to minimize the cost of operation, considering reliability aspects, has been proposed in this work. A mixed integer linear programming (MILP) model for optimal placement of DGs along with switches and tie-lines is proposed in [8].

An algorithm for the enhancement of network resilience has been introduced in [9]. An artificial hummingbird algorithm for optimal placement of renewable sources is presented in [10]. Network reconfiguration of radial distribution systems for the enhancement of voltage has been discussed in [11]. An optimal placement of DGs for the enhancement of reliability has been discussed in [12]. Optimal placement of DGs considering the CIGRE benchmark has been explained in [13]. Optimal placement of DG considering network reconfiguration for reliability improvement is discussed in [14]. Optimal placement of a wind farm for reliability enhancement is shown in [15]. Optimal placement of DG for stability improvement is discussed in [16].

Optimal placement of tie-lines and DGs to minimize post-outage operations is discussed [17]. Optimal placement of renewable sources in a microgrid is discussed in [18]. The result in [19], a method to improve distribution system reliability, has been discussed using the distributed generators available in the system. A multi-objective planning of DGs and renewables in a microgrid is proposed in [20]. A mixed integer linear programming (MILP) technique for optimal placement of charging stations is proposed in [21]. Dynamic network reconfiguration in coordination with switchable capacitor banks has been discussed in [22]. Simultaneous placement of shunt capacitors and DG units has been proposed in [23]. Harris Hawks' optimization for optimal placement of DGs is discussed in [24]. Renewable DG integration to grid has been discussed in [25]. DG placement considering a large scale disturbance is discussed in [26]. Optimal sizing and placement of renewables using metaheuristic technique has been discussed in [27].

Most of the work available in the literature is on single DG placement, and mostly heuristic techniques have been used. Novelty in this paper is multiple DG placement in a multi-feed system and solving the problem using a novel approach called actor-critic (AC) learning algorithm. AC is an extension to the reinforcement learning (RL) algorithm, which is based on the Markov decision process (MDP) [28]. RL can be expected to give gratifying results in the case of a complex problem having a large number of states. The remaining content of the paper is divided into the following sections: i) Section 2 brief about the proposed methodology; ii) Section 3 deals with problem formulation; iii) Section 4 describes the solution methodology; iv) Section 5 followed by a discussion on the results; v) Section 6 gives the conclusion of the work.

## 2. REINFORCEMENT LEARNING

Reinforcement learning (RL) is a goal-directed method that tackles a problematic situation through interaction. It basically consists of an agent and an environment. The learner and decision maker is known as the agent, and everything outside it is known as the environment. RL maps the situations to actions to enhance the reward signal. During the learning process, the agent gets information about the present environment's state, $s_t \in S$ at time step '$t$'. On the basis of this state agent decides the action, $a_t \in A(s_t)$ to be taken and receives a reward, $r_{t+1}$ one time step later and enters into a new state $s_{t+1}$. This is shown in Figure 1.

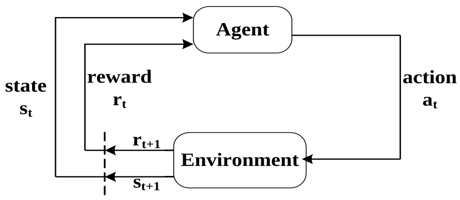


Figure 1. Architecture of reinforcement learning

This process of the agent deciding the action to be taken, the environment reciprocating to these actions and presenting new rewards and states takes place for each time step and during each time step, the agent does mapping between the present state and the probability of deciding each possible action when the agent is in this state. This mapping is known as Agent's Policy, represented as $\pi(s_t, a_t)$. Agent, based on the experience changes its policy. The objective of the RL agent is to maximize the sum of rewards over the long run. These reinforcement learning algorithms use the value function, $V^\pi(s)$, to estimate "how good it is for the agent to take a particular action for a present state". $V^\pi(s)$ represents the expected value of return when the system begins in state $s$ and then follows a policy $\pi$. Mathematically, this can be represented as (1).

$$V^\pi(s) = E_\pi\{R_t|s_t = s\} = E_\pi\{\sum_{j=0}^{\infty} \gamma^k r_{t+j+1}|s_t = s\} \quad (1)$$

Where, $V^\pi(s)$ is the value function of a policy $\pi$, $E_\pi$ is the expected value for a given policy, $\gamma$ is the discount factor, and $r_{t+j+1}$ is the reward gained when agent moves from state $s_{t+j}$ to state $s_{t+j+1}$. Solving a problem using reinforcement learning involves finding an optimal value function, which is expressed as (2).

$$V^*(s) = max(V^\pi(s)), \quad \forall \ s \in S \tag{2}$$

Where, $V^*(s)$ is the optimal value function.

## 3. PROPOSED METHODOLOGY

The DG placement problem in this work is solved using the actor-critic (AC) learning method. AC learning method is an extension to the reinforcement learning problem. AC learning embeds reinforcement learning in it. In actor-critic architecture, the policy selects actions, hence, it is termed as an actor, and the estimated value function is termed as the critic, as it criticizes the actions taken by the policy. Learning is done in an on-policy manner, the critic must learn about and must criticize the policy that is presently followed by the actor. The criticism made is in the form of temporal difference (TD) error, hence, this method comes under temporal difference methods. TD error acts as a scalar signal for the output given by critic and helps in learning process that takes place between actor and critic as shown in Figure 2.

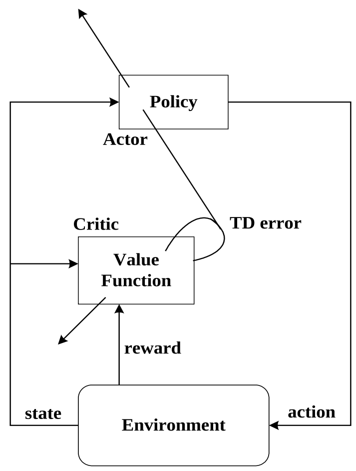


Figure 2. Architecture of actor-critic learning

Mathematically TD error, $\delta_t$ is given as (3).

$$\delta_t = r_{t+1} + \gamma V(s_{t+1}) - V(s_t) \tag{3}$$

Where, $\delta_t$ is temporal difference and $r_{t+1}$ is the reward gained when agent moves from $s_t$ to $s_{t+1}$ state. If TD error is positive, the tendency to select an action $a_t$ in future should be strengthened and if it is negative the tendency to select an action $a_t$ in future should be weakened. This is done by updating the tendency as (4).

$$p(s_t, a_t) \leftarrow p(s_t, a_t) + \beta\delta_t \tag{4}$$

Where, $p(s_t, a_t)$ is the tendency to select an action $a_t$ in future when state is $s_t$ and $\beta$ is the step size parameter. Policy is evaluated using Gibbs softmax method as (5).

$$\pi_t(s, a) = \frac{e^{p(s,a)}}{\sum_{b=1}^{B} e^{p(s,b)}} \tag{5}$$

Where, $\pi_t(s, a)$ is the policy corresponding to state $s_t$ and action $a_t$. The state values are updated as (6).

$$V(s_t) \leftarrow V(s_t) + \alpha\delta_t \tag{6}$$

Where, $\alpha$ is the step size parameter.

## 4. PROBLEM FORMULATION

It is assumed that the distribution system and the DGs to be placed in the system are owned by the same utility. This paper focuses on finding the suitable locations ($DG_{loc}$) and sizes ($DG_{size}$) of DGs in each feeder that reduce the total system real power loss (TPL). Mathematically, it can be expressed as (7).

$$Min\{TPL(DG_{loc}, DG_{size})\} \tag{7}$$

Subject to below mentioned constraints.

### 4.1. Voltage constraints

Installation of DG, though reduces real power loss compared to the base case, sometimes it may result in voltage violations at some buses. Hence, there is a need to put a constraint on the node voltages. Substation buses are taken as reference, and voltages at these buses are maintained at 1 p.u. In accordance with ANSI C84.1, voltages at remaining buses are constrained amid 0.95 p.u. and 1.05 p.u. [29], [30]. That can be expressed as (8).

$$0.95 \le V_n \le 1.05 \tag{8}$$

Where, $V_n$ is the voltage at load bus $n$.

### 4.2. Real and reactive power balance

According to IEEE Std 1547-2003 [31], DG connected in the distribution system should operate at unity power factor. Therefore, the real power consumed by load and losses in each feeder is fed from grid and DG, connected to the respective feeder, whereas reactive power load and associated losses are supplied by the grid alone. Hence, the power balance equations for real and reactive powers can be expressed as (9)-(10).

$$P_{grid_m} + P_{DG_{m,n}} = P_{load_m} + P_{loss_m} \tag{9}$$

$$\text{and} \quad Q_{grid_m} = Q_{load_m} + Q_{loss_m} \tag{10}$$

Where, $P_{grid_m}$ is the real power supplied by the grid to feeder $m$, $P_{DG_{m,n}}$ is MW capacity of DG placed at bus $n$ in feeder $m$, $P_{load_m}$ is the real power load connected to feeder $m$, $P_{loss_m}$ is the real power loss in feeder $m$, $Q_{grid_m}$ is the reactive power supplied by the grid to feeder $m$, $Q_{load_m}$ is the reactive power load connected to feeder $m$, and $Q_{loss_m}$ is reactive power loss in feeder $m$.

### 4.3. DG power constraints

DG solution resulted from the optimization algorithm should be a positive value and it should be a less than a maximum value. Hence, this condition can be expressed as (11).

$$0 \le P_{DG_{m,n}} \le P_{DG_{max}} \tag{11}$$

Where, $P_{DG_{max}}$ is the maximum limit of $P_{DG}$.

## 5. SOLUTION METHODOLOGY

This paper discusses multiple DG placements in a multi-feed system. The objective is to place a DG in each feeder at an optimal location with an optimal size that minimizes the total system losses. In case of a multi-feed system, the situations, possible load in each feeder, and the actions to be taken, a combination of DG locations and sizes of it in each feeder, will increase with the increase in the size of the system. In such a situation, it would be better to use a technique that decides on the solution by mapping existing states with possible actions. The reinforcement algorithm maps the states to actions and maximizes the values of a policy that leads to maximum expected return. AC algorithm is an improvement to reinforcement learning, and since it embeds the features of both dynamic programming and Monte-Carlo methods. This method has been adopted to solve the problem of DG installation.

### 5.1. Evaluation of states

A standard 16-bus distribution system with 3 feeders, shown in Figure 3, is used to apply the actor-critic learning approach for minimization of total system real power losses. In this figure, solid lines encircled with numbers 1-13 are sectionalizing branches, and the dashed lines encircled with numbers 14-16 are tie branches of the system for the base case. Total power losses produced in the system for each possible DG location and quantum represent states. Location set $\{b_1, b_2, b_3\}$ represents a state in this paper, where:

$$b_1 = \{n \ \ \forall\, n \ = \ 4,\ 5,\ 6,\ 7\} \tag{12}$$

$$b_2 = \{n \ \ \forall\, n \ = \ 8,\ 9,\ 10,\ 11,\ 12\} \tag{13}$$

$$b_3 = \{n \ \ \forall\, n \ = \ 13,\ 14,\ 15,\ 16\} \tag{14}$$

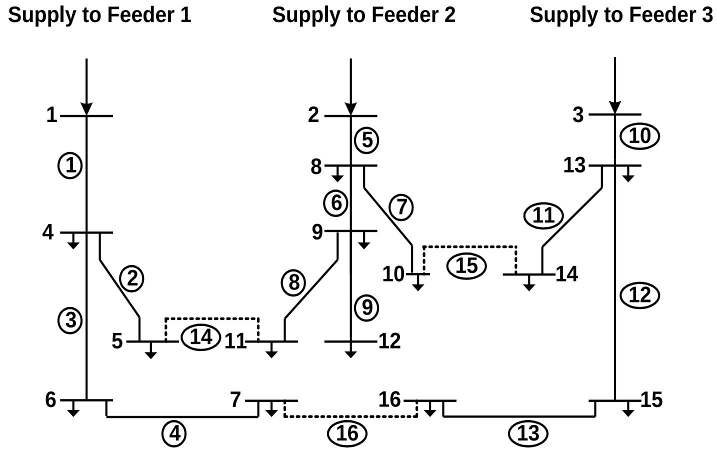


Figure 3. Single line diagram of a 16-bus radial distribution system

### 5.2. Evaluation of actions

In this paper, DG-connected bus behaves like a PQ bus. The minimum value of DG capacity is taken as 0 MW. 0 MW indicates a case of no DG placement. The maximum capacity of DG in each feeder is limited to 30% of the load in the feeder to make proper utilization of the present substation sunk cost [32]. DG sizes are chosen to be positive integers from a practical point of view. The Cartesian product of location set $\{b_1, b_2, b_3\}$ and DG capacity set $\{c1, c2, c3\}$ represents the possible actions in this paper. Real power load on feeder 1, feeder 2, and feeder 3 are 8.5 MW, 15.1 MW, and 5.1 MW, respectively.

### 5.3. Evaluation of rewards

For each state-action pair, real power losses are evaluated for the best configuration of the system. Reciprocal of total system real power losses is taken as a reward for a particular state-action pair.

$$r_{t+1} = \frac{1}{TPL} \tag{15}$$

The mathematical procedure of agent making transition between different states, by taking actions according to the policy (actor) and correction of these actions by value function (critic) is given in flowchart in Figure 4. For the policies and values obtained using the actor-critic algorithm, the optimum value is obtained using (2). State-action pair corresponding to this optimal value, known as optimal policy, $\pi^*$ gives the DG solution for each feeder.

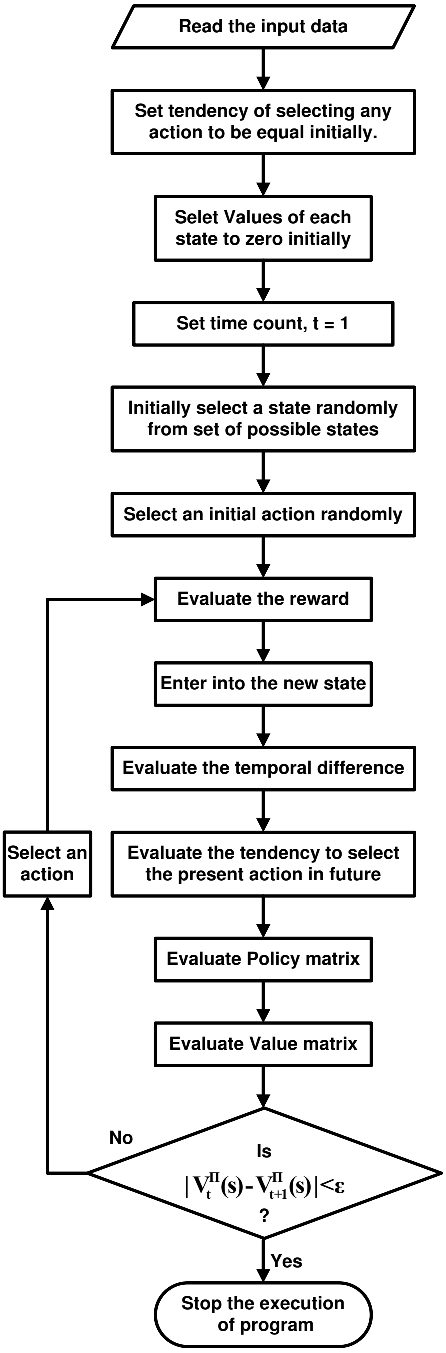


Figure 4. Flowchart for actor-critic learning method

## 6. RESULTS

The information obtained for DG solution in each feeder using AC approach is shown in Table 1. The voltage profiles at various buses before and after the placement of DG is shown as a plot in Figure 5. Voltages at substation buses are maintained at 1 p.u. Apart from the substation buses, there is a significant improvement in voltages at other buses. Real power loss in the system and minimum node voltage in the system, with and without DG, are shown in Table 2. Percentage reduction in losses compared to the base case without DG is found to be 48.35% and the minimum node voltage has improved from 0.9568 p.u. to 0.9710 p.u. after placement of DG.

Table 1. Optimum location and size of DGs

| Feeder no. | Optimum location | Optimum size (MW) |
|---|---|---|
| 1 | 7 | 3 |
| 2 | 12 | 5 |
| 3 | 16 | 2 |

Table 2. Total real power loss and minimum node voltage

| Case | Total real power loss in MW | Minimum node voltage (p.u.) |
|---|---|---|
| Without DG | 0.5995 | 0.9568 |
| With DG | 0.3097 | 0.9710 |

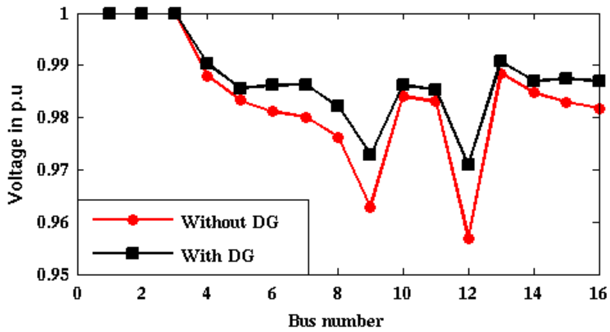


Figure 5. Voltages at various buses with and with out DGs in a 16-bus distribution system

## 7. CONCLUSION

In case of a multi-feed system, the problem of multiple DG placement comes out with several combinations of DG locations and sizes. Reinforcement learning and actor-critic learning algorithms have a feature of mapping situations with possible actions. These algorithms find a potential application in case of complex and uncertain situations. Actor-critic learning algorithm embeds the features of reinforcement learning, dynamic programming, and Monte-Carlo approaches. Hence the problem of optimal placement of DGs in a multi-feed system is solved in this paper using actor-critic learning algorithm. In actor-critic learning algorithm, actions taken by the policy (actor) are corrected by the value function (critic). The approach is applied to a standard 16-bus radial distribution system for minimization of system real power losses. The results obtained are discussed for both the cases of with and without DG.

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| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Neelakanteshwar Rao Battu | ✓ | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | |
| Surender Reddy Salkuti | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |

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|---|---|---|
| C : **C**onceptualization | I : **I**nvestigation | Vi : **Vi**sualization |
| M : **M**ethodology | R : **R**esources | Su : **Su**pervision |
| So : **So**ftware | D : **D**ata Curation | P : **P**roject Administration |
| Va : **Va**lidation | O : Writing - **O**riginal Draft | Fu : **Fu**nding Acquisition |
| Fo : **Fo**rmal Analysis | E : Writing - Review & **E**diting | |

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## INFORMED CONSENT

Informed consent is not applicable to this paper as no personal information of anybody is used in this work.

## ETHICAL APPROVAL

Ethical approval is not applicable to this paper as the proposed work doesn't use people or animals.

## DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SRS], upon reasonable request.

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## BIOGRAPHIES OF AUTHORS

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