Automatic Voltage Regulator Control Simulation Analysis using Differential Evolution Algorithm

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Abstract

The focus of this research was to determine whether and how distributed generation (DGs) could help with voltage control (VC) in medium voltage distribution grids through reactive power generation and absorption. The control technique was described using the optimal power flow problem, with a focus on voltage control. DGs are used in this work to simulate voltage control with the intention of minimizing active power loss while improving the network voltage profile. This study employs a Differential Evolution (DE) approach to determine the optimal solution with benefits and potential potency and introspective acumen. The effectiveness of the optimizer is analyzed, and its superiority over Genetic algorithm (GA) is illustrated using substantial statistical analysis. In this study, the IEEE 33-bus is used as a test system.

Keywords: Voltage Control, Genetic algorithm, Distributed Generation

1. Introduction

Voltage instability, or the inability of a bus voltage to return to its original or acceptable value as a result of a disturbance, is one of the leading causes of voltage collapse, which can result in a power system outage.The majority of the outages were caused by voltage instability, which was caused by the control system's inability to pull enough reactive power to support the voltage at critical grid buses [1, 2]. The use of reactive power resources is a common method of controlling voltage in power systems. It protects against fast voltage changes over a short period of time, such as a few seconds, which controls the magnitude of the load bus voltage. The control is implemented by adjusting the bus voltage that has the greatest influence [3, 4].

How the system is partitioned and which pilot bus is used heavily influence the use of a Voltage strategy and sensitivity analysis was used to select the pilot buses for each partition [5–7]. In Italy, a similar hierarchical control architecture has been implemented [8, 9].Once the tertiary voltage regulator minimizes the differences between real field measurements and ideal projected references, the master regulator set-point values are reset [10]. The European hierarchical voltage control system is made up of geographically dispersed regulators that were typically built on the basis of offline investigations and later became fixed distribution entries [11].

The juncture correlation, which was used in the vast bulk of power networks worldwide in the previous century, is insufficient to ensure smart grid features. Due to the high cost of phasor measurement units, previous research focused on employing a variety of optimization methods to reduce the number of phasor measurement units while maintaining complete detection accuracy of the power system[12, 13]. Many researchers have investigated the use of optimization techniques in the VC, such as optimizing the collaboration of tap changers, autonomous regulators, and solar power generation [14, 15], in which only the use of Distributed Energy Resources (DER) that affect the designated region is optimized, and the distribution grid is divided into smaller sections that are optimized separately. Decentralized optimization is another approach [16–18]. Offline optimization for the entire grid is performed using finite data sets in this case, and look-up tables for each inverter-based DER are developed so that they can run solely.

The preceding studies show that voltage regulation for distribution systems is an ongoing problem. As a result, the following are the work's objectives: Proper voltage control using DGs with the goal of lowering active power loss and improving voltage profile. The proposed optimizer's performance is evaluated, and its superiority over Differential Evolution (DE) and the Genetic Algorithm (GA) is demonstrated using extensive statistical analysis. The IEEE 33-bus is used as a test system in this study.

2. Differential Evolution Algorithm

DE is a parallel direct search method that uses parameter vectors in MC E-dimensions as a population for each generation GP

$$X_{i,GP}\ ,\ I = 1, 2, ..., MC \tag{1}$$

The initial vector population is generated at random and should encompass the entire parameter space.

If a preliminary solution is available, the initial population could be formed by multiplying the nominal solution $X_{nom,0}$ by normally distributed random deviations.

DE creates new parameter vectors by multiplying a third vector by the weighted difference between two population vectors. This is known as mutation. The altered vector's properties are then combined with those of another preset vector, the target vector, to form the trial vector.

The target vector $X_{I,GP}$, i = 1, 2, ..., MC,r is formed:

$$QP_{I,GP+1} = x_{r1,GP} + FP \cdot (X_{r2,GP} - X_{r3,GP}) \tag{2}$$

with random indexes r1, r2, r3 1, 2, ...MC, integer, individually unique, and FP>0. FP, a real and constant factor [0, 2], regulates the amplification of the differential variation ($X_{r2.GP}$ $X_{r3,GP}$) To make the altered parameter vectors more diverse, crossover is used. To do this, the trial vector is formed:

$$PP_{I,GP+1} = (PP_{1/,GP+1}, PP_{2I,GP+1}, ..., p_{Di,GP+1}) \tag{3}$$

is formed, where

(if (randb(JB) $\geq$ CRP) or JB = rnbr(I)

JP = 1, 2, ...E.

$PP_{JI,GP+1}$ = if (*randb(JB) > CRP)* and *JB s rnbr(I),* (4)

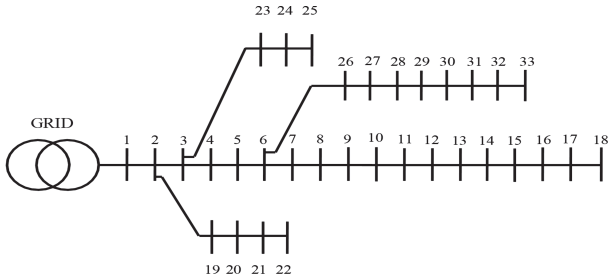

Figure 1: IEEE 33 bus test system

here the Jth evaluation of a uniform random number generator with a result of [0.1] is called *randb(JB)*. The user must specify the crossover constant [0.1], represented by CRP. The index rnbr(I) 1, 2, ..., E was picked at random. This ensures that $QP_{i,G+1}$. sends $PPI_{,GP+1}$ at least one parameter.

To evaluate if the trial vector $PP_{I,GP+1}$ should belong to generation $GP + 1$, it is tested against the target vector $X_{I,GP}$ using the greedy criteria. If the vector $PP_{I,GP+1}$ has a lower cost function value than the vector $A_{I,GP}$, then$X_{I,GP}$ is set to *PPI, GP;* otherwise, the original value *XI,GP* is kept.

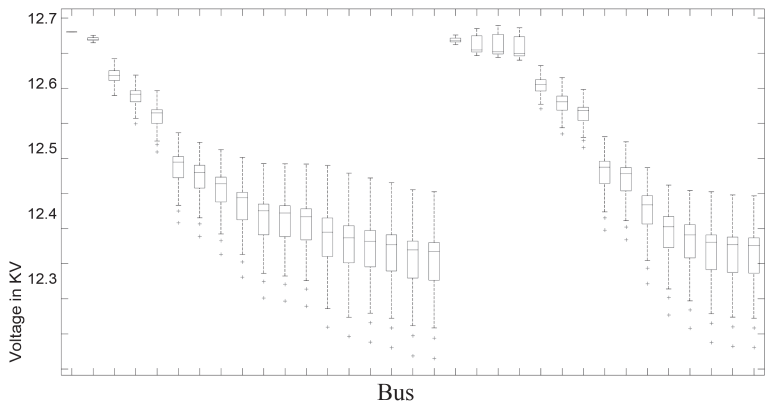

Figure 2: Voltage curve after integrating DGs

3. Modelling and Simulation

A power system's voltage and reactive power control hierarchy is made up of the following components:

The first level focuses on controlling the generator's terminal voltage with an automatic voltage regulator (AVR). This tier has the fastest response time when compared to the other two. The control is accomplished

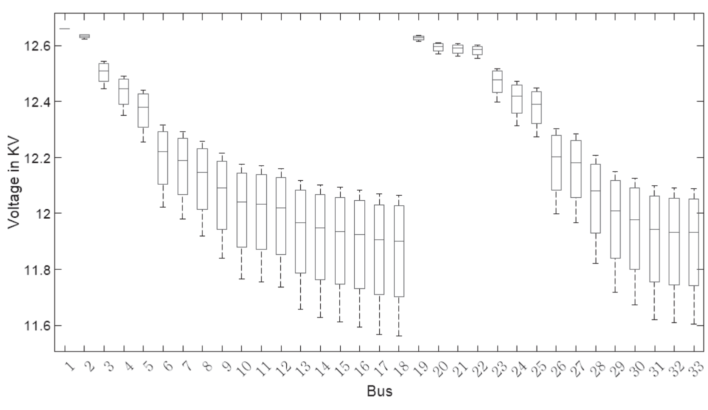

Figure 3: Voltage curve before integrating DGs

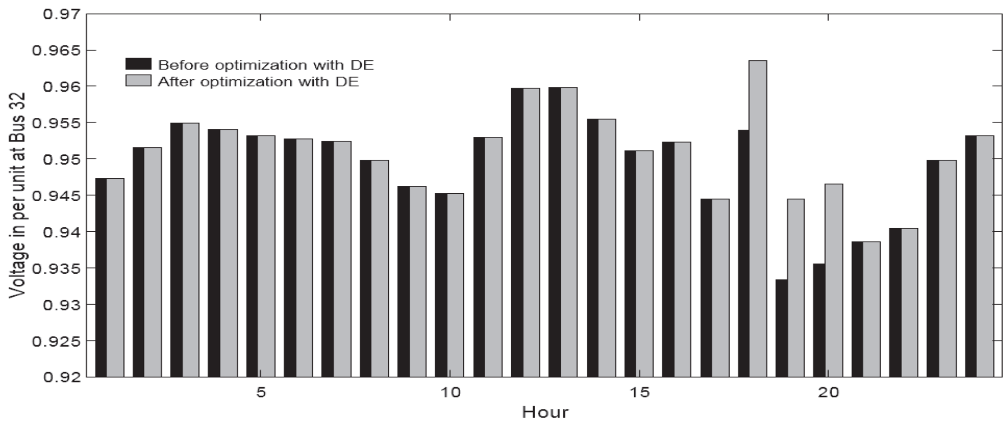

Figure 4: Voltage at bus 32 after optimization

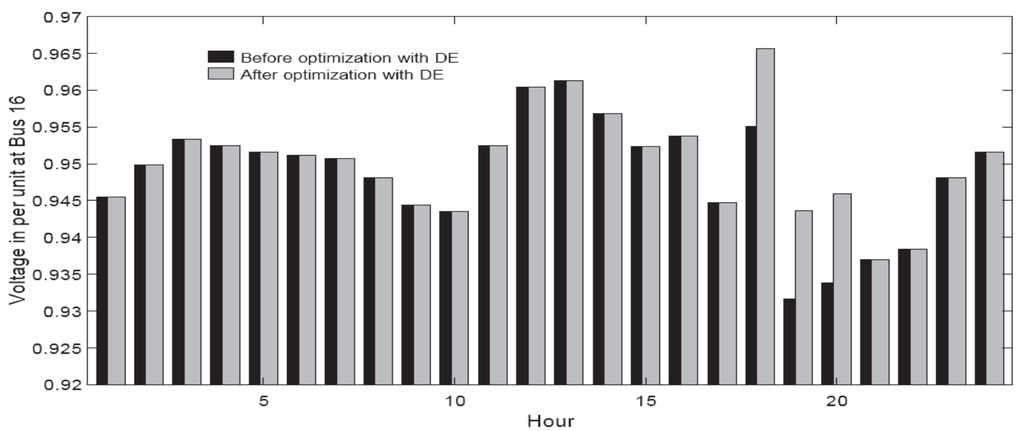

Figure 5: Voltage at bus 16 after optimization

by adjusting the field current of the generator. The second level targets the cluster control , which controls reactive power. If the grid is divided into multiple regions, a few regional voltage regulators are used.

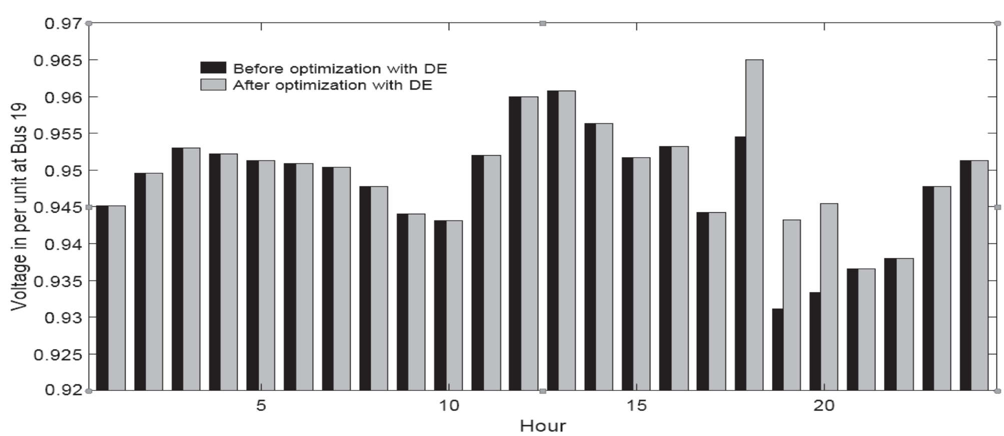

Figure 6: Voltage at bus 19 after optimization

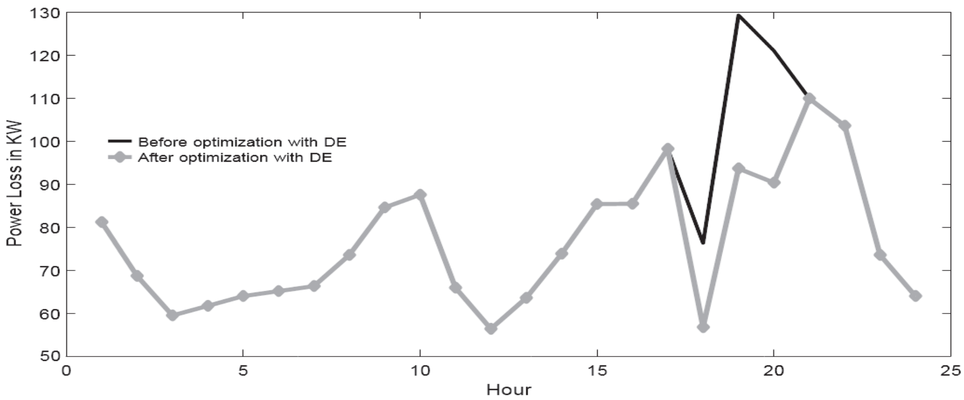

Figure 7: Active power loss curve

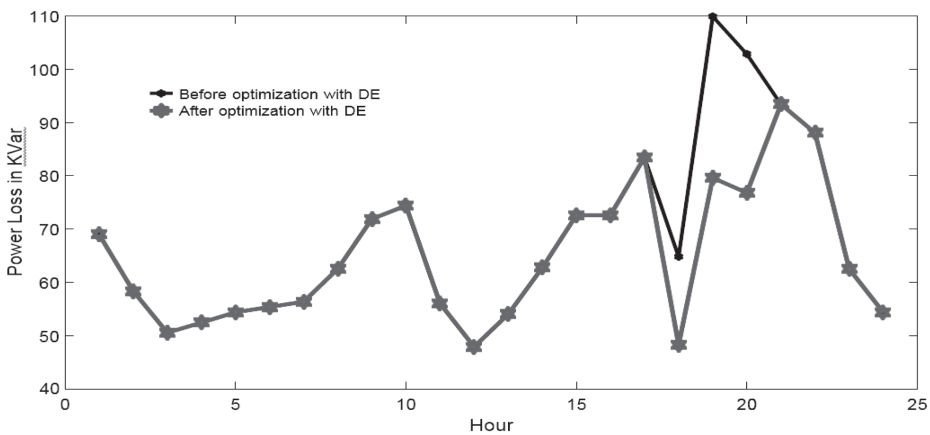

Figure 8: Reactive power loss curve

The objective function developed in this work aims to provide the grid with the maximum allowable reactive power from DGs while minimizing total energy loss and maximizing the system voltage profile.

The evaluation criteria can be grouped together to form a single objective function.

$$\text{OBjective} = \text{minimize}(\text{ActivePowerLoss}) \tag{5}$$

where,

$$\textit{Active Power Loss} = \sum_{AA=1}^{KK} SS_{AA}(V_Y^2 + V_U^2 - 2V_Y V_U \cos(\alpha_Y - \alpha_U)) \tag{6}$$

SS_{AA} is a AA line conductance, where AA is a line number between buses Y and U. V_Y and αY signify the voltage and angle at bus Y, respectively.

3.1. Simulation Procedure

For the purpose of this work, IEEE 33 bus is used as test systems. The IEEE 33 bus system has a total load demand of 3.715 MW and 2.3 MVar. The control technique described below was developed and implemented in the experimental scenario for the study grid mentioned in the preceding sections. If the voltage for the tertiary voltage control falls below 0.95 p.u., the optimization algorithm is run. If the optimization algorithm does not converge to the best solution, the constraints remain within their limits, and the solution is accepted despite being suboptimal, the solver should be adjusted or modified, or no action is taken. The operation is carried out every hour.

4. Results and Analysis

Figure 2 and Figure 3 show the voltage profile of DG integrated IEEE 33 over a 24-hour period. A margin of 0.95 p.u. (per unit) is used to detect the buses' vulnerability. This means that buses with an average voltage of less than 0.95 p.u. are classified as vulnerable and subject to optimization. To ensure a fair comparison, the total number of iterations and starting population size for each island are kept consistent across all three approaches. Furthermore, the maximum number of iterations is used as the algorithm's halting condition. Furthermore, in terms of elapsed time, DA outperforms GA. DE outperforms GA in terms of average, best, and worst fitness values. As a result, in terms of fitness function value and computational performance, DE outperforms all other algorithms.

Table 1: Statistics of DE, GA

Index	DE	GA
Minimum Power Loss (kW)	55	77
Minimum Power Loss (kW)	62.6	83.5
Average Power Loss (kW)	58.8	79.4
Computational time (s)	14	26

The above-mentioned control method resulted in local optimum voltage profiles that met the criteria at all of the buses. Figures 4-6 contrasts and compares the optimized voltage profiles of buses 32, 16 and 19. The optimized voltage profiles are greater than 0.95 p.u. as a result of objective function optimization, indicating that only the truly necessary control actions are performed to meet the scheme pilot's prerequisites. Furthermore, as shown in Figure 7, Table 1, when the optimization process is used, active power losses in the grid are reduced by approximately 5.6 percent. Similarly, DE reduces active power loss to base loss in the IEEE 33 bus system by 73.6%, making it the best of all algorithms. The optimized reactive power production profiles are shown in Figure 8. Because control actions are usually required in that region , the majority of the generated reactive power is deposited at the feeder's end during non-optimized hours. DGs are urged to provide their highest reactive power reserves during the hours when optimization is required.

This implies that the provided experimental grid has only a limited amount of voltage control via reactive power. They can, on the other hand, be used to shape voltage profiles. Furthermore, by taking into account the constraints, overall active power losses are minimized.

5.Conclusion

Using optimization approaches in distribution networks, this research provides a unique method for voltage control. The suggested DE method was compared to the results of one other algorithms, GA. IEEE 33 bus is used as test systems. According to the results, DE beats all of the algorithms for all of the objectives and both test systems. As a result, the proposed VC method may be used in a real-world power distribution system using DGs.

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