Optimal Location and Sizing of Shunt Capacitors and Distributed Generation in Power Distribution Systems

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ABSTRACT

This paper proposes a novel approach to determine an optimal location and sizing of shunt capacitors for reactive power compensation in power distribution systems with distributed generation. Here, the optimal location for installing the shunt capacitors is determined using the loss sensitivity factor approach. The stochastic nature of distributed generation (i.e., wind and solar PV power) is considered in this paper. Optimal sizing of shunt capacitors has been determined by considering the power loss minimization as an objective function and this problem is solved using the differential evolution algorithm (DEA). The results obtained with DEA are also compared with genetic algorithm (GA) and particle swarm optimization (PSO) algorithms. The effectiveness of this proposed approach has been simulated on the IEEE 15, 33, 69, and 85 bus test systems.

Keywords: Distributed Generation, Shunt Capacitors, Optimal Location and Sizing, Loss Reduction, Evolutionary Algorithms, Renewable Energy

1. INTRODUCTION

The optimal operation of power transmission and distribution networks is becoming increasingly challenging. Recently, renewable energy has been growing rapidly. It is now contributing significantly to existing power systems. Network loading is increasing steadily and flow patterns are becoming less predictable as renewable energy sources (RESs) replace conventional power generation. During the last decade and in the foreseeable future, wind and solar energy sources are set to have a significant growth rate around the world. With the incorporation of RESs into existing systems, we must reduce the transmission and distribution losses. Methods for optimal location and sizing of shunt capacitors for reactive power compensation in distribution systems have attracted a lot of attention from distribution companies with the incorporation RESs. The optimal placement and capacity of these devices have direct effects on the system's performance. An overview of distributed generation (DG), the advances in DG technology, and different optimization methods used for optimal placement and the sizing problem have been presented in references [1, 2].

Often distributed power generation increases the number of controllable devices in the system dramatically. Favorable economics have facilitated the deployment of RESs at transmission and distribution levels. Now economic and reliability issues are emerging due to the intermittent nature of renewable power generation. An exact mixed-integer nonlinear programming approach for optimal location and sizing of capacitor banks in power distribution networks is proposed in [3]. An optimization algorithm for the improvement of power quality using optimal location and sizing of active power conditioner and shunt capacitors in radial distribution systems (RDSs) is proposed in [4]. An optimal way to determine locations and sizes of shunt capacitors and DGs in RDSs systems with an objective of minimizing line losses is proposed in [5–7]. In [8] proposes an approach to determine the optimal locations of DG by using a Kalman filter algorithm. A new stochastic framework based on a point estimate method for solving capacitor placement problems considering wind turbines in the system is proposed in [9]. A voltage stability index based approach which utilizes the combined sensitivity factor analogy to optimally locate and size a multi-type DG in the 48-bus Belin distribution system with the aim of reducing losses and improving the voltage profile is proposed in [10]. In [11], an optimal DG and capacitor planning problem has been solved using the hybrid weight improved particle swarm optimization and gravitational search algorithms.

In [12], a multi-location DG placement problem is solved by minimizing total active power loss in RDSs by using a genetic algorithm (GA). Optimal reactive power sizing for power system operation enhancement using grey wolf optimization is proposed in [13]. In [14], optimal sizing of DG is proposed with the objective of minimizing DG cost and maximizing loadability value. An approach for simultaneous

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allocation of capacitor banks and DG by taking into account the stochastic nature of DG is proposed in [15]. In [16], an optimization problem is solved by considering the number of distributed generators and reactive power sources in selected buses of a RDS.

From the above literature review, it is obvious that there is a pressing requirement for determining the optimal location of shunt capacitors in radial distribution systems (RDSs) with renewable energy sources (RESs). In this paper, the loss sensitivity factor approach is used to determine the optimal bus selection for the placement of shunt capacitors (i.e., reactive power compensation). Here, the vector based distribution load flow (VDLF) is used for determining the loss sensitivity factors. For determining the optimal reactive power sizing, the electrical power loss minimization is considered as an objective function to be optimized and it is solved by using the differential evolution algorithm (DEA). The validity and effectiveness of proposed approach was tested on four standard (i.e., IEEE 15, 33, 69, and 85 bus) radial distribution systems.

The remainder of this paper is organized as follows: Section 2 presents the optimal of shunt capacitors using loss sensitivity factors approach. Modelling of wind and solar energy systems is described in Section 3. The proposed approach for solving the optimal reactive power sizing using differential evolution algorithm is presented in Section 4. Simulation results and discussions are presented in Section 5. Finally, the contributions with concluding remarks are presented in Section 6.

2. OPTIMAL LOCATION OF SHUNT CAPACITORS USING THE LOSS SENSITIVITY FACTORS APPROACH

In this paper, the optimal allocation of shunt capacitors in RDSs with the objective of minimizing power loss of the system when subjected to equality and inequality constraints is proposed. Reactive power compensation at potential buses is required for voltage profile improvement at various buses of the distribution network. Loss sensitivity factors offer important information about the sequence of potential buses for reactive power compensation in the system. These factors are determined using the single run of the base case load flow study. A new methodology is used to determine the candidate nodes for reactive power compensation using loss sensitivity factors [16]. The estimation of these candidate buses helps reduce the search space for the optimization procedure. A distribution line connected between bus i and bus j is depicted in Fig. 1.

Active power loss in the k^{th} distribution line is expressed using

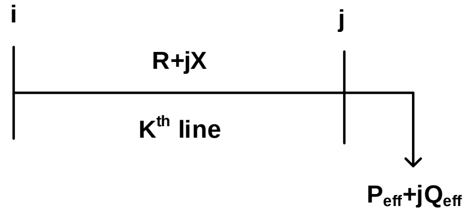

Fig.1: *Distribution line connected between buses i and j.*

$$P_{loss}(j) = \frac{\left[P_{eff}^2(j) + Q_{eff}^2(j)\right] R(k)}{V(j)^2} \quad (1)$$

Similarly, the reactive power loss in the k^{th} distribution line is expressed using [17]

$$Q_{loss}(j) = \frac{\left[P_{eff}^2(j) + Q_{eff}^2(j)\right] X(k)}{V(j)^2} \quad (2)$$

where P_{eff}^2 and Q_{eff}^2 are the total effective active and reactive powers supplied beyond the bus j. Loss sensitivity factors for active and reactive power losses are expressed using

$$\frac{\partial P_{loss}}{\partial Q_{eff}} = \frac{2Q_{eff}(j)R(k)}{V(j)^2} \quad (3)$$

$$\frac{\partial Q_{loss}}{\partial Q_{eff}} = \frac{2Q_{eff}(j)X(k)}{V(j)^2} \quad (4)$$

2.1 Candidate Bus Selection using the Loss Sensitivity Factors Approach

The loss sensitivity factors $\partial P_{loss}/\partial Q_{eff}$ are calculated from the base case load flows and these values are arranged in descending order for all the lines of a given distribution network. A bus position vector $B_{pos}(i)$ is used to store the respective 'end' buses of the lines arranged in descending order of $\partial P_{loss}/\partial Q_{eff}$ values. The descending order of $\partial P_{loss}/\partial Q_{eff}$ elements of the bus position vector will decide the sequence in which the buses are to be considered for the compensation. This sequence is purely governed by $\partial P_{loss}/\partial Q_{eff}$. At these buses of the $B_{pos}(i)$ vector, the normalized voltages $V_{norm}(i)$ are calculated by considering the base case voltage magnitudes and they are expressed using [18, 19]

$$V_{norm}(i) = \frac{V(i)}{0.95} \quad (5)$$

The buses whose $V_{norm}(i)$ values are less than 1.01 are considered as candidate buses that need reactive power compensation. These candidate buses are stored in the $rank_{bus}(i)$ vector. Here, the loss sensitivity factors are used to decide the sequence in which the buses are to be considered for compensation placement. Whether a bus requires reactive power compensation or not is decided by the value of the $V_{norm}(i)$ vector. If the voltage at a bus in the sequence is healthy (i.e., $V_{norm}(i) > 1.01$) such a bus requires no compensation and it will not be listed in the $rank_{bus}(i)$ vector. The $rank_{bus}(i)$ vector provides the information about potential, or candidate, buses for reactive power compensation [20].

3. MODELING AND UNCERTAINTY HANDLING OF WIND AND SOLAR ENERGY SYSTEMS

3.1 Modelling of Wind Energy System

WEG converts the kinetic energy of wind into electrical energy. The output power of WEG at a specific location depends on wind speed at hub height and speed characteristics of the turbine. The power output of WEGs varies accordingly to the wind speed, and it closely follows the Weibull probability distribution function. The power output of WEG (P_W) (i.e., wind speed to wind power conversion function) is expressed using

$$P_W = \begin{cases} 0 & \text{if } v < v_{ci} \text{ or } v \geq v_{co} \\ P_r \left(\dfrac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} \right) & \text{if } v_{ci} \leq v \leq v_r \\ P_r & \text{if } v_r \leq v \leq v_{co} \end{cases} \tag{6}$$

where v is wind speed in m/s. v_r, v_{ci}, and v_{co} are the rated, cut-in, and cut-out wind speeds in m/s. P_r is the rated power output. The power output from WEG (P_W) is limited by the upper/maximum power limit $P_W^{\max}$ and it is expressed as

$$P_W \leq P_W^{\max} \tag{7}$$

As mentioned earlier in this work, the Weibull probability density function (PDF) of wind speed is used and it is expressed as

$$f_v = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right]; \quad 0 < v < \infty \tag{8}$$

where c and k are scale and shape factors, respectively. Generally, c ranges from 10 to 20 miles per hour and k ranges from 1.5 to 2.5.

For the probability distribution function in a continuous range (i.e., $v_{ci} \leq v \leq v_r$), the random variable transformation is used. By using linear variable transformation, it can be expressed as

$$f_{P_W} = \frac{k\,(v_r - v_{ci})}{C^k P_r}\left[v_{ci} + \frac{P_W}{P_r}(v_r - v_{ci})^{k-1}\right] \cdot \exp\left[-\left\{v_{ci} + \frac{P_W\,(v_r - v_{ci})}{P_r}\right\}^k\right] \tag{9}$$

3.2 Modeling of Solar Energy System

The solar energy system directly converts energy from the sun's rays into electricity. The solar PV power output depends on natural conditions such as solar irradiation and temperature at a certain time and at a specific location. It is expressed as

$$P_S = f(G, T) \tag{10}$$

However, temperature is not considered in this paper. The obtained power output from a solar PV unit depends on solar irradiance and it is expressed as,

$$P_S = \begin{cases} P_r^S \left(\dfrac{G}{G_{std} R_c}\right) & \text{if } 0 < G < R_c \\ P_r^S \left(\dfrac{G}{G_{std}}\right) & \text{if } G > R_c \end{cases} \tag{11}$$

where G is the forecasted solar irradiation. G_{std} is the standard solar irradiation 1000 W/m^2. P_r^S is the rated power generation from the solar PV unit. R_c is a certain solar irradiation set at 150 W/m^2. The power output from a solar PV generator (P_S) is limited by maximum/upper limit $P_S^{\max}$ and it is expressed as

$$P_S \leq P_S^{\max} \tag{12}$$

The hourly solar irradiance mostly follows a bimodal distribution and it can be considered as a linear combination of two unimodal distribution functions. These unimodal functions are modelled using log-normal, Weibull, and Beta probability density functions (PDFs). In this paper, it is modelled using a Weibull distribution and it can be expressed as

$$\begin{aligned} f_G = {} & W\left(\frac{k_1}{c_1}\right)\left(\frac{G}{c_1}\right)^{k_1-1} \exp\left[-\left(\frac{G}{c_1}\right)^{k_1}\right] \\ & + (1-W)\left(\frac{k_2}{c_2}\right)\left(\frac{G}{c_2}\right)^{k_2-1} \exp\left[-\left(\frac{G}{c_1}\right)^{k_2}\right] \end{aligned} \tag{13}$$

where W is the weight parameter, and it is in the range of $0 < W < 1$. c_1, c_2, k_1, and k_2 are the scale and shape factors, respectively.

4. OPTIMAL REACTIVE POWER SIZING USING DIFFERENTIAL EVOLUTION ALGORITHM (DEA)

The Differential Evolution Algorithm (DEA) is a stochastic, population-based evolutionary optimization technique which was introduced by Storn and Price in 1995. DEA was developed to optimize the real parameter and real valued functions. It can be used for solving various practical problems considering non-linear, non-continuous, non-differential, and

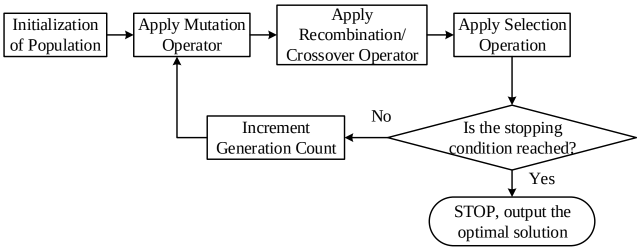

Fig.2: *Overview of Differential Evolution Algorithm (DEA).*

multi-dimensional features. The probabilistic distribution for the generation of offspring is not required for DEA. This leads to a lower computational burden and fewer mathematical operations. An overview of DEA is depicted in Fig. 2 [24].

As mentioned earlier, DEA is a population-based optimization technique which consists of initialization, mutation, crossover, and selection operators. A brief description of these operators is presented next.

4.1 Initialization

Define each chromosome/variable of population for a given problem between their lower (x_j^L) and upper (x_j^U) bounds, i.e.,

$$x_j^L \leq x_{j,i} \leq x_j^U \tag{14}$$

Randomly initialize a population of chromosomes of size N. Initialize the population members using

$$x_{j,i}(0) = x_j^L + rand\left(x_j^U - x_j^L\right) \tag{15}$$

where $rand$ is a random number between 0 and 1.

4.2 Mutation Operation

The main aim of the mutation operator is to expand the search space. For a given chromosome $x_{j,i}$, randomly select three vectors $x_{r1,i}$, $x_{r2,i}$, and $x_{r3,i}$ in such a way that i, $r1$, $r2$, and $r3$ are distinct. Then, add the weighted difference of two vectors to the third one using [25]

$$v_i^{j+1} = x_{r1,j} + k\left(x_{r2,j} - x_{r3,j}\right) \tag{16}$$

where k is a mutation factor between 0 and 2, and v_i^{j+1} is the donor vector.

4.3 Crossover Operation

There are two variants of crossover operators available in the literature: binomial crossover and exponential crossover. In this paper, binominal crossover is used. By using this crossover operator, the generated child $U_{i,i}(t)$ is expressed as

$$U_{i,i}(t) = \begin{cases} v_{i,j}(t) & \text{if } rand_{j,i} \leq CR \\ x_{i,j}(t) & \text{if } rand_{j,i} > CR \end{cases} \tag{17}$$

where CR is the crossover rate, and $U_{i,i}(t)$ is the child which will compete with the parent $x_{i,j}(t)$.

4.4 Selection Operation

In the selection process, DEA uses the Survival of fittest principle. This process is carried out to keep the population size constant and to find the child and parent chromosomes which will be selected for the next generation [25].

$$x_i^{t+1} = \begin{cases} U_i(t) & \text{if } f(U_i(t)) \leq f(x_i(t)) \\ x_i(t) & \text{otherwise} \end{cases} \tag{18}$$

where $f(\cdot)$ is the objective function to be optimized/minimized. The mutation, crossover, and selection operators will continue to be applied until the stopping criterion is reached. For a detailed description of DEA, the reader may refer to the references [24, 25].

Once the $rank_{bus}(i)$ vector (i.e., where capacitive shunt compensation is to be placed) is identified using the loss sensitivity factors approach, then the DEA is used to determine the optimum shunt capacitor size at each potential/candidate bus, indicated by $rank_{bus}(i)$. After placing the estimated shunt capacitive value at the most preferred bus (i.e., at a candidate bus), again DEA is executed for fixing the optimum capacitor size at the next preferred candidate/potential bus [26]. This procedure is repeated until no additional compensation is required and any further compensation increases the losses in the distribution network. At this stage, the algorithm is stopped. Here, the vector based distribution load flow (VDLF) is used for solving the RDS load flow and then the loss sensitivity factor approach is utilized for optimal bus selection (i.e., for reactive power compensation) [27]. As mentioned earlier, the amount of reactive power size to be injected at the candidate buses is determined using the DEA by considering power loss minimization as the objective function to be optimized. The power loss minimization function is formulated as [28, 29]

$$\text{minimize}\left(P_{loss}(j) = \frac{\left[P_{eff}^2(j) + Q_{eff}^2(j)\right]R(k)}{V(j)^2}\right) \tag{19}$$

4.5 Algorithm for Reactive Power Sizing using Differential Evolution Algorithm (DEA)

The step-by-step algorithm for solving the optimal sizing of reactive power compensation problem in the RDSs using DEA is presented next:

Step 1: Read the system data and the data related to wind and solar energy systems.

Step 2: Run the base case vector based distribution load flow (VDLF) and determine the active power loss (P_{loss}) from this VDLF [30].
Step 3: Identify the potential buses for reactive power compensation using the loss sensitivity factor approach.
Step 4: Determine the number of candidate/potential buses and their location using a loss sensitivity factor approach [31, 32].
Step 5: Read the data related to Differential Evolution Algorithm (DEA), i.e., string length (S_{len}), population size (P_{size}), crossover constant (K_{CR}), scale constant (F), maximum number of generations ($N_{gen}^{\max}$), and maximum and minimum limits of reactive power generations ($Q_{\max}$ and $Q_{\min}$). Initially, set previous generation best compensation (g_c) = 0 and previous generation best fitness (g_{best}) = 0. Initialize fitness = zeros (1, P_{size}).
Step 6: Randomly generate the initial population using

$$Q_{new} = Q_{\min} + rand() * (Q_{\max} - Q_{\min}) \tag{20}$$

The command $rand()$ generates a random number between 0 and 1 [33].
Step 7: Start the generation loop of DEA.
Step 8: Apply the mutation operator using Eq. (16).
Step 9: Apply the crossover operator using Eq. (17).
Step 10: Enforce the minimum and maximum reactive power limits ($Q_{\min}$ and $Q_{\max}$).
Step 11: At the i^{th} candidate bus, place the obtained reactive power compensation (Q_{comp}) obtained from Step 10.
Step 12: Run the vector based distribution load flow (VDLF) and calculate the active power loss (P_{loss}). Evaluate the fitness value using [34]

$$fitness = \frac{1}{1 + P_{loss}} \tag{21}$$

Step 13: Restore the actual reactive power load at the i^{th} candidate bus.
Step 14: Apply the selection operation using Eq. (18).
Step 15: Sort the chromosomes in descending order of their fitness values.
Step 16: Check for convergence, then determine the error (i.e., the difference of fitness of first chromosome to the fitness of last chromosome). If the error is less than the epsilon, then the problem has converged, so corresponding reactive power compensation value (i.e., Q_{comp}) is stored and the algorithm continues on Step 17. Otherwise, goto Step 18.
Step 17: Place the Q_{comp} at the i^{th} candidate bus and goto Step 19.
Step 18: Increment the generation count (N_{gen}). If $N_{gen} = N_{gen}^{\max}$, then go to Step 20, otherwise goto Step 8.
Step 19: If the saving in active power loss is greater than 1.5 kW, then goto Step 11. Otherwise, goto Step 21.
Step 20: Problem is not converged in $N_{gen}^{\max}$.
Step 21: STOP and display the results.

5. RESULTS AND DISCUSSION

The proposed approach was tested on standard IEEE 15, 33, 69, and 85 bus test systems including wind and solar energy systems. As mentioned earlier, DEA is used for solving the optimal shunt capacitor sizing at potential buses. The considered DEA parameters are: population size is 30, crossover constant (CR) is 0.75, and scale constant (F) is 0.75 [35]. In this paper, the parameters related to WEGs are: $v_{ci} = 4$ m/s, $v_{co} = 25$ m/s and $v_r = 14$ m/s. The solar irradiation at the considered hour is 450 W/m^2 [36].

5.1 Simulation Results on IEEE 15 Bus System

In this test system, one wind energy generator is placed at bus number 5 and one solar PV unit is placed at bus number 13. Table 1 presents the comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 15 bus radial distribution system (RDS). Minimum and maximum voltages, and active power losses obtained before and after placing shunt capacitors at optimal locations are presented in Table 1. Optimal locations obtained using DEA for reactive power compensation are 6, 11, and 8 buses. The corresponding reactive power sizing is 478.2 kVAR, 482.5 kVAR and 250.1 kVAR, respectively. The reduction in active power losses after placing the shunt capacitors was reduced to 60.32% from the base case (i.e., power losses before placing the shunt capacitors) power losses. The simulation results obtained with DEA are also compared with results using the GA and PSO algorithms, and all results are presented in Table 1.

5.2 Simulation Results on IEEE 33 Bus System

In this test system, two wind energy generators are placed at buses 10 and 14, and two solar PV units are placed at buses 23 and 30. Table 2 presents the comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 33 bus RDS. Minimum and maximum voltages, and active power losses obtained before and after placing shunt capacitors at optimal locations are presented in Table 2. Optimal locations obtained using DEA for reactive power compensation are 8, 28, and 31 buses. The corresponding reactive power sizing is 510.6 kVAR, 528.7 kVAR and 539.4 kVAR, respectively. The reduction in active power losses after placing the shunt capacitors has been reduced to 37.6% from the base case (i.e., power losses before placing the shunt capacitors) power losses.

Table 1: *Comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 15 bus radial distribution system (RDS).*

Technique	$V_{\min}$ (p.u.)	$V_{\max}$ (p.u.)	Optimal location for compensation (bus number)	Reactive power size (kVAR)	Active power loss (kW)	Loss reduction from base case
Base case	0.9102	0.9980	—	—	60.56	—
GA	0.9301	0.9972	6 11 12	480.6 485.3 251.8	26.85	55.66%
PSO	0.9336	0.9969	4 10 11	484.0 487.7 250.9	25.54	57.83%
DEA	0.9389	0.9986	6 11 8	478.2 482.5 250.1	24.03	60.32%

Table 2: *Comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 33 bus radial distribution system (RDS).*

Technique	$V_{\min}$ (p.u.)	$V_{\max}$ (p.u.)	Optimal location for compensation (bus number)	Reactive power size (kVAR)	Active power loss (kW)	Loss reduction from base case
Base case	0.9036	0.9971	—	—	200.82	—
GA	0.9534	0.9986	8 29 27	512.7 534.2 541.6	131.5	34.52%
PSO	0.9589	0.9986	6 28 29	520.8 535.2 538.1	129.4	34.56%
DEA	0.9601	0.9988	8 28 31	510.6 528.7 539.4	125.32	37.6%

Table 3: *Comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 69 bus radial distribution system (RDS).*

Technique	$V_{\min}$ (p.u.)	$V_{\max}$ (p.u.)	Optimal location for compensation (bus number)	Reactive power size (kVAR)	Active power loss (kW)	Loss reduction from base case
Base case	0.9092	0.9999	—	—	241.92	—
GA	0.9714	0.9999	62 42 63 53 64	282.4 137.5 346.7 279.3 498.1	155.65	35.6%
PSO	0.9728	0.9999	46 69 58 60 63	388.0 156.5 142.2 400.6 415.2	154.02	36.33%
DEA	0.9749	1.000	53 46 50 62 67	318.8 346.0 146.1 350.9 108.6	152.54	36.95%

Table 4: *Comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 85 bus radial distribution system (RDS).*

Technique	$V_{\min}$ (p.u.)	$V_{\max}$ (p.u.)	Optimal location for compensation (bus number)	Reactive power size (kVAR)	Active power loss (kW)	Loss reduction from base case
Base case	0.9132	0.9925	—	—	312.85	—
GA	0.9523	0.9956	18 52 24 8 35	256.1 321.8 610.3 423.0 158.9	158.42	49.36%
PSO	0.9578	0.9985	10 56 82 27 42	365.1 340.8 231.7 468.2 498.5	154.64	50.57%
DEA	0.9595	0.9999	8 56 17 29 61	269.1 331.7 416.0 455.3 496.4	152.51	51.25%

The simulation results obtained using the DEA are also compared with results using the GA and PSO algorithms, and all results are presented in Table 2.

5.3 Simulation Results on IEEE 69 Bus System

In this test system, three wind energy generators are placed at buses 15, 35, and 47. Three solar PV units are placed at buses 18, 39, and 55. Table 3 presents the comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 69 bus RDS. Minimum and maximum voltages, and active power losses obtained before and after placing shunt capacitors at optimal locations are presented in Table 3. Optimal locations obtained using DEA for reactive power compensation are 53, 46, 50, 62, and 67 buses, and the corresponding reactive power sizing is 318.8 kVAR, 346.0 kVAR, 146.1 kVAR, 350.9 kVAR and 108.6 kVAR, respectively. The reduction in active power losses after placing the shunt capacitors has been reduced to 36.95% from the base case (i.e., power losses before placing the shunt capacitors) power losses. The simulation results obtained with DEA are also compared with results using the GA and PSO algorithms, and all results are presented in Table 3.

5.4 Simulation Results on IEEE 85 Bus System

In this test system, four wind energy generators are placed at buses 12, 28, 54, and 70. Four solar PV units are placed at buses 18, 24, 59, and 68. Table 4 presents the comparison of different techniques for optimal placement and sizing of shunt capacitors in IEEE 85 bus RDS. Minimum and maximum voltages, and active power losses obtained before and after placing shunt capacitors at optimal locations are presented in Table 4. Optimal locations obtained using DEA for reactive power compensation are 8, 56, 17, 29, and 61 buses, and the corresponding reactive power sizing is 269.1 kVAR, 331.7 kVAR, 416.0 kVAR, 455.3 kVAR and 496.4 kVAR, respectively. The reduction in active power losses after placing the shunt capacitors has been reduced to 51.25% from the base case (i.e., power losses before placing the shunt capacitors) power losses. The simulation results obtained with DEA are also compared with results using the GA and PSO algorithms, and all results are presented in Table 4.

6. CONCLUSION

In this paper, a method for computing an optimal location and sizing of shunt capacitors for reactive power compensation problem is presented. The problem was solved by considering the distributed generation in the radial distribution system (RDS). Here, the optimal location of shunt capacitors was determined using the loss sensitivity factors approach. The converged vector based distribution load flow (VDLF) solution is used for calculating the loss sensitivity factors. After determining the potential buses for reactive power compensation, the differential evolution algorithm (DEA) is used to find the optimal capacitor sizes in the RDS with distributed generation. The simulations are performed on IEEE 15, 33, 69, and 85 bus RDSs with wind and solar energy generators placed at different buses in the system. The results show significant reduction in system power losses and improvements in the system voltage profile. The results obtained with DEA are also compared with those found with the genetic algorithm (GA) and particle swarm optimization (PSO) algorithms. The results show the effectiveness and superiority of the approach proposed in this paper.

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