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A New Hybrid Evolutionary Algorithm for Daily Volt/var Control in Distribution Networks Considering Distributed Generators

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Abstract: This paper presents a new approach for daily Volt/VAr control in distribution systems including Distributed Generators (DGs). Since the high R/X ratio of distribution networks, the effects of DGs on Volt/Var control are much more than other equipments. In this paper, a price-based approach is defined to settle on the optimum active and reactive power dispatch for the DGs, the reactive power contribution of the capacitor banks, and the tap settings of the transformers in a day in advance. A hybrid evolutionary algorithm based on combination of differential evolution (DE) and ant colony optimization (ACO) algorithms, named ACO-DE, is utilized to solve the daily Volt/Var control which is a non-linear mixed integer problem. The proposed algorithm is tested on two distribution test systems.

Key words: Ant Colony Optimization (ACO), Distributed Generators, Differential Evolution (DE) Voltage and Reactive Power Control

INTRODUCTION

Distributed generators generate electricity from many small energy sources. They reduce the amount of energy lost in transmitting electricity because their generated energy is generated very near where it is used. They also decrease the size and number of power lines that must be constructed.

Studies carried out by researching centers show that DGs participation in energy production will be more than 25 percent in the near future (Hartikainen, T., 2007). Therefore, it is necessary to study the impact of DGs on the power systems, especially on the distribution networks.

Since the X/R ratio of distribution lines is small and the configuration of distribution network is radial, the daily Volt/Var control is one of the most important control schemes in the distribution networks, which can be affected by DGs. The daily Volt/Var control is defined as regulation of voltage over the feeders and reactive power (or power factor) at the substation bus (Baron, M.E. and M.Y. Hsu, 1999). The control is achieved by adjusting the Load Tap Changer transformers (LTCs), Voltage Regulators (VRs) and capacitor banks as control variables to minimize an objective function considering the constraints. Many researchers have investigated reactive power and voltage control in distribution networks.

In (Baron, M.E. and M.Y. Hsu, 1999), Baran *et al*, presented a supervisory Volt/Var control scheme, based on the new measurements and computer resources available at the substation bus. They obtained the new measurements based on the fact that the voltage drop on the feeder varies linearly with the total feeder load current measured at the substation (Baron, M.E. and M.Y. Hsu, 1999). Roytelman, et al presented a centralized Volt/Var control algorithm for the distribution system management. The paper considered the summation of power losses and power demands as the objective functions (Roytelman, I., 1995). The supervisory control schemes for integrated Volt/Var control at the substation and feeders were discussed in (Borozan, V., 2001). The supervisory controller, located at substation, coordinates the control of local regulating devices based on dynamically changing system conditions. An approach for modeling local controllers and coordinating the local and centralized controllers at the distribution system management was given by Roytelman and Ganesan (2000) and (Roytelman and V. Ganesan, 2000). A heuristic and algorithmic combined approach for reactive power control optimization with time varying load in distribution systems was presented in (Deng, Y., 2002). Volt/Var control in distribution systems using a time-interval was described by Hu *et al* (2003). The goal was to determine optimum dispatch schedules for on-load tap changer (OLTC) settings at the substations and all of

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shunt capacitors switching based on the day-ahead load forecast. A genetic algorithm based procedure was used to determine both the load level partitioning and the dispatch scheduling. An improved evolutionary programming and its hybrid version combined with the nonlinear interior point technique to solve the optimal reactive power dispatch problems was proposed in (Lu, W.Y.S. and D.C. Yu, 2004). Niknam et al presented methods for the Volt/Var control in radial distribution networks considering Distributed Generations. They considered electrical power losses as the objective function and used the genetic algorithm and hybrid An Ant Colony Optimization (ACO) evolutionary algorithm in order to solve the problem, but they did not consider the impact of active power of DGs on Volt/Var control. Niknam proposed a cost-based compensation methodology for daily Volt/Var control in distribution networks including DGs (Niknam, T., 2008). In the proposed method, the objective function includes the cost of electrical energy provided by DGs and distribution companies during the next day. ACO has been used to solve the problem. Niknam et al presented an approach for daily Volt/Var control in a radial distribution network with DG units (Niknam, T., 2008). In the method, the power factors of DGs have been considered to be constant. A hybrid evolutionary optimization algorithm according to combing PSO and ACO has been used to solve the problem.

Carvalho et al illustrated the problem of voltage rise mitigation in distribution networks with distributed generation. The goal of the proposed approach is not to put DG in control of bus voltage but the aim is to assure that injections alone do not cause significant voltage perturbations(Carvalho, P.M.S., 2008). Madureira and Lopes presented a methodology for coordinated voltage support in distribution networks with large integration of distributed generation and microgrids. The objective function is to minimize active power losses and microgeneration shedding (Madureira, A.G., 2009). Viawan and Karlsson presented the impact of DG to the available voltage and reactive power control also they proposed a proper coordination strategy among DG and other traditional voltage and reactive power control equipment(Viawan, F.A. and D. Karlsson, 2008). The electrical power losses have been considered as the objective function. Su proposed several voltage control strategies that incorporate existing voltage control device and reactive power compensator(Su, C.L., 2009). Senjyu et al proposed an optimal control of distribution voltage considering DGs with coordination of distributed installations, such as the load ratio control transformer, step voltage regulator, shunt capacitor, shunt reactor, and static var compensator (Senjyu, T., 2008). They considered voltage variation and electrical power losses as the objective function. Hong and Luo presented a method using wind generator voltages, static compensators, and transformer taps as controllers to regulate the voltage profile for operation planning in a distribution system (Hong, Y.Y. and Y.F. Luo, 2009). In references (Carvalho, P.M.S., 2008)-(Hong, Y.Y. and Y.F. Luo, 2009), the active power of DGs which has more impact on voltage profile has not been considered.

In this paper, a novel network-based daily Volt/VAr control strategy is presented for a distribution network including DG units. According to private ownership of the DGs, a price-based control methodology is proposed as a proper criterion for real reactive power control of the DG units of the distribution system. Based on the proposed algorithm, the objective function which is to be minimized is the total costs offered by the DG units and the distribution companies, during the next day. The control variables in the proposed algorithm are active power components of the DGs, power factors of the DGs, reactive power components of the capacitor banks, and tap settings of the transformers in the next day. It should be noted that in this paper, it is assumed that there are many distribution companies with different offers.

Due to presence of the DGs, LTCs, VRs, etc., the daily Volt/VAr control of a distribution network has conventionally been considered as a mixed-integer nonlinear programming problem. Classical methods such as linear programming, mixed-integer programming, quadratic programming, etc. can be used o solve this problem. However, in some cases, the foregoing methods fail to provide the global minima and only reach local minima. Moreover, some classical methods cannot handle the integer problems (Lu, W.Y.S. and D.C. Yu, 2004). The two foregoing shortcomings can be overcome if an evolutionary method is utilized to solve the optimization problem (Lu, W.Y.S. and D.C. Yu, 2004). In this paper, a hybrid evolutionary algorithm based on combination of ACO and DE algorithms has been utilized as the optimization method for solving the control problem. It is demonstrated that the proposed method results in a superior performance as compared to the existing methods, and also numerically converges more quickly than the evolutionary methods such as the genetic algorithm (Niknam, T., 2005; Niknam, T., 2008).

The main contributions of the paper are as follows: (i) present a price based compensation methodology for daily Volt/Var control in distribution networks considering DGs, (ii) consider the active power and power factor of DGs as control variables and (iii) present a hybrid ACO and DE algorithm to solve the Volt/Var control.

Formulation of Daily Volt/var Control in Dirtribution Networks Considering Dgs:

The daily Volt/Var control in distribution networks considering DGs is a nonlinear optimization problem with continuous and discrete parameters and variables. The objective function and constraints are presented as follows:

Objective Function:

In this paper, the proposed objective function includes the following two parts:
Cost of electrical energy generated by distribution companies.
Cost of electrical energy generated by DGs.
The objective function of daily Volt/Var control is defined as:

$$f(X) = \sum_{t=1}^{Nd} \{ \sum_{i=1}^{Nsub} (\Pr ice_i^t \times P_{Sub,i}^t) + \sum_{i=1}^{N_g} (\Pr ice_{dg,i}^t \times P_{gi}^t) \} \times \Delta t_t \tag{1}$$

$$X = [\overline{Tap}, \overline{Q_G}, \overline{U_C}, \overline{P_G}]$$

$$\overline{Tap} = [\overline{Tap_1}, \overline{Tap_2}, ..., \overline{Tap_{Nt}}]$$

$$\overline{Tap_i} = [Tap_i^1, Tap_i^2, ..., Tap_i^{Nd}]; \quad \mathrm{i} = 1,2,3,...,\mathrm{N_t}$$

$$\overline{Q_G} = [\overline{Q_{g1}}, \overline{Q_{g2}}, ..., \overline{Q_{gNg}}]$$

$$\overline{Q_{gi}} = [Q_{gi}^{\ 1}, Q_{gi}^{\ 2}, ..., Q_{gi}^{\ Nd}]; \qquad \mathrm{i} = 1,2,3,...,\mathrm{N_g}$$

$$\overline{P_G} = [\overline{P_{g1}}, \overline{P_{g2}}, ..., \overline{P_{gNg}}]$$

$$\overline{P_{gi}} = [P_{gi}^{\ 1}, P_{gi}^{\ 2}, ..., P_{gi}^{\ Nd}]; \qquad \mathrm{i} = 1,2,3,...,\mathrm{N_g}$$

$$\overline{U_C} = [\overline{U_{c1}}, \overline{U_{c2}}, ..., \overline{U_{cNc}}]$$

$$\overline{U_{ci}} = [U_{ci}^{\ 1}, U_{ci}^{\ 2}, ..., U_{ci}^{\ Nd}]; \qquad \mathrm{i} = 1,2,3,...,\mathrm{N_c}$$

where:
N_c number of capacitors.
N_g: number of DGs.
N_d *:* number of load variation steps.
N_t *:* number of transformers
t: an index which represents time steps of load level.

X state variables vector

$\overline{Tap}$: tap vector representing tap position of all transformers in the next day.

$\overline{Tap_i}$: tap vector including tap position of the ith transformer in the next day.

Tap_i^t : tap position of the ith transformer for the tth load level step.

$\overline{Q_G}$: DGs reactive power vector including reactive power of all DGs in the next day.

$\overline{Q_{gi}}$: DGs reactive power vector including reactive power of the ith DG in the next day.

$Q_{gi}^{\ t}$: reactive power of the ith DG for the tth load level step.

$\overline{P_G}$: DGs active power vector including active power of all DGs in the next day.

$\overline{P_{gi}}$: DGs active power vector including active power of the i^{th} DG in the next day.

${P_{gi}}^t$: active power of the i^{th} DG for the t^{th} load level step.

${U_{ci}}^t$: state of the i^{th} capacitor in the light of turning on and off during time "t" ,which equals 0 or 1.

$\overline{U_{ci}}$: capacitors switching vector including state of the i^{th} capacitor in the next day.

$\overline{U_C}$: capacitors switching state vector including state of all capacitors in the next day.

Δt_t: time interval.

$\mathrm{Pr}ice^t$: electrical energy price generated by the distribution company for the t^{th} load level step.

${P_{Sub}}^t$: active power of distribution company for the t^{th} load level step.

$Price_{dg,i}^t$ the electrical energy price offered by the i^{th} DG for the t^{th} load level step.

In this problem, it is assumed that tap position of transformers changes stepwise. In the objective function formula, ${P_{Sub}}^t$ is considered as a slag bus and calculated based on state variables for the t^{th} load level step.

Constraints:

Constraints are defined as follows:Active and reactive power constraints of DGs:

$$({P_{gi}}^t)^2 + ({Q_{gi}}^t)^2 \le S^2{}_{gi,\max} \tag{2}$$

$S_{gi,max}$ is the apparent power of the i^{th} DGs.Distribution line limits:

$$\left|P_{ij}^{Line}\right|^t < P_{ij,\max}^{Line} \tag{3}$$

$\left|P_{ij}^{Line}\right|^t$ and $P_{ij,\max}^{Line}$ are the absolute power flowing over distribution lines and maximum transmission power between the nodes *i* and *j,* respectively.Tap of transformers:

$$Tap_i^{\min} < Tap_i^t < Tap_i^{\max} \tag{4}$$

$Tap_i^{\min}$, $Tap_i^{\max}$ and Tap_i^t are the minimum, maximum and current tap positions of the i^{th} transformer, respectively.Unbalanced three-phase power flow equations.

Maximum allowable daily operating times of transformers:

$$DOT_i^{Trans} \le MADOT_i^{Trans} \tag{5}$$

DOT_i^{Trans} and $MADOT_i^{Trans}$ are the daily operating times and maximum allowable daily operating

times of the i[th] transformer, respectively.
Maximum allowable daily operating times of capacitors:

$$(\sum_{t=1}^{Nd} U_{ci}^{t} \leq MADOT_i^{Cap} \quad \text{i=1,2,3,…,Nc}) \tag{6}$$

$MADOT_i^{Cap}$ is the maximum allowable daily operating times of the i[th] capacitor.

Substation power factor

$$Pf_{\min} \leq Pf^{t} \leq Pf_{\max} \tag{7}$$

$Pf_{\min}$, $Pf_{\max}$ and Pf^{t} are the minimum, maximum and current power factor at the substation bus during time t.Bus voltage magnitude

$$V_{\min} \leq V_i^{t} \leq V_{\max} \tag{8}$$

V_i^t , V_{max}, V_{min} are the voltage magnitudes of the i[th] bus during time "t" and the maximum and minimumvalues of voltage magnitudes, respectively.

The Effect of Dgs on Voltage Profile of Distribution:

Connecting a DG to the distribution network will affect the flow of power and the voltage profiles. As the X/R ratio of the distribution lines is small, the DG has much impact on voltage profiles. To demonstrate this, consider a 2-bus test system (Fig.1) (Niknam, T., 2005).

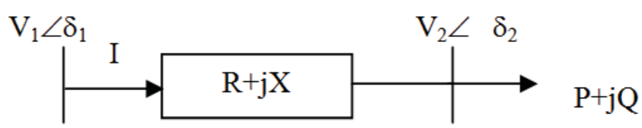

Fig. 1: A two-bus test system

The voltage drop along the line from bus 1 to bus 2 is calculated as follows:

$$\begin{aligned}
&\Delta V = V_1\angle\delta_1 - V_2\angle\delta_2 = (R + jX)I \\
&I = \frac{P - jQ}{V_2^*} \\
&P = P_g + P_{Load} \\
&Q = Q_g + Q_{Load} \\
&|\Delta V|^2 = \frac{(RP + XQ)^2 + (XP - RQ)^2}{V_2^2} \approx \frac{(RP + XQ)^2}{V_2^2}
\end{aligned} \tag{9}$$

where V_i and δ_i are the magnitude and angle of voltage at the ith bus, and P_g , Q_g , P_{Load} and Q_{Load} are the active and reactive powers of the DG and load, respectively. $R + jX$ is the line impedance.

As indicated in the above equation, neither RP nor XQ is negligible. Also, since the X/R ratio is small and Q is less than P, the impacts of DGs active powers have much more than their reactive power.

Ant Colony Algorithm:

Ants are insects which live together. Since they are blind animals, they find the shortest path from their nest to food with the aid of pheromone. Pheromone is the chemical material deposited by the ants, which serves as critical communication medium among ants, thereby guiding the determination of the next movement. On the other hand, ants find the shortest path based on intensity of pheromone deposited on different paths. Assume that ants want to move from point A to B (Fig. 2).

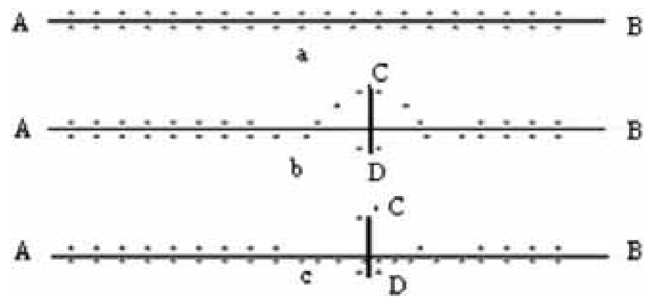

Fig. 2: An example of finding the shortest path by ants

At first, if there is no obstacle, all of them will move along the straight path (AB) (Fig.2.a). At the next stage, assume that there is an obstacle; in this case, ants will not be able to follow the original trail in their movement. Therefore, randomly, they turn to the left (ACB) or to the right (ADB) (Fig2.b). Since ADB path is shorter than ACB, the intensity of pheromone deposited on ADB is more than the other path. So ants will be increasingly guided to move on the shorter path (Fig2.c). This behavior forms the fundamental paradigm of the ant colony system.

As was indicated in Fig.2, the intensity of deposited pheromone is one of the most important factors for ants to find the shortest path. Generally, the intensity of pheromone and path length are two important factors that should be used to simulate the ant system. To select the next path, the state transition probability is defined as follows:

$$P_{ij} = \frac{(\tau_{ij})^{\gamma_2}(1/L_{ij})^{\gamma_1}}{\sum_{\substack{j=1 \\ j\neq i}}^{N}(\tau_{ij})^{\gamma_2}(1/L_{ij})^{\gamma_1}} \tag{10}$$

Where: t_{ij} and L_{ij} are the intensity of pheromone and the length of path between nodes *j* and *i*, respectively. g_1 and g_2 are the control parameters for determining the weight of trail intensity and length of path, respectively. *N* is the number of ants.

After selecting the next path, the trail intensity of pheromone is updated as:

$$\tau_{ij}(k+1) = \rho\tau_{ij}(k) + \Delta\tau_{ij} \tag{11}$$

In the above equation, r is a coefficient such that (1-r) represents the evaporation of the trail between time k and k+1 and $\Delta\tau_{ij}$ is the amount of pheromone trail added to τ_{ij} by ants.

To apply the ACO algorithm for clustering, the following steps have to be taken (Senjyu, T., 2008):
Step1: Generate the initial population and trail intensity
Step 2: Generate the initial population and trail intensity for ants in each colony (local search)
Step 3: Determine the next position
Step 4: Check the convergence condition

Application of Aco-de to Daily Volt/var Control:

In this section, a new hybrid approach based on the ant colony algorithm and the differential algorithm is presented to solve the daily Volt/Var control considering DGs. In order to follow this goal, a number of N colonies are considered. To choose a movement direction, each colony needs to find the best local and global positions as follows:

Finding the Best Global Position:

Suppose the i^{th} colony wants to change its position. At first, the transition probabilities between the i^{th} and j^{th} colonies are calculated as indicated in (4).

$$\left[P_{Gn}\right]_i = [P_{Gi1}, P_{Gi2}, \ldots, P_{GiN}]_{1*N}$$
$$P_{Gij} = \frac{(\tau_{Gij})^{\gamma_2}(1/L_{ij})^{\gamma_1}}{\sum_{j=1}^{N}(\tau_{Gij})^{\gamma_2}(1/L_{ij})^{\gamma_1}} \tag{12}$$

where P_{Gij} is the transition probability between the i^{th} and j^{th} individuals.
The cumulative probabilities are calculated as:

$$[C_{Gn}]_i = [C_{G1}, C_{G2}, \ldots, C_{GN}]_{1*N}$$
$$where$$
$$C_{G1} = P_{Gi1}$$
$$C_{G2} = C_{G1} + P_{Gi2}$$
$$....$$
$$C_{Gj} = C_{Gj-1} + P_{Gij}$$
$$....$$
$$C_{GN} = C_{GN-1} + P_{GiN} \tag{13}$$

In above equations, C_{Gj} is cumulative probability for the j^{th} individual. The roulette wheel is used for stochastic selection of the best global position as follows:

A number between 0 and 1 is randomly generated and compared with the calculated cumulative probabilities. The first term of cumulative probabilities (C_{Gj}), which is greater than the generated number, is selected and the associated position is considered as the best global position.

Finding the Best Local Position:

By using the DE algorithm, the best local position is found around the i^{th} colony.

Determination of the next Position:

The movement direction for each colony is obtained from linear combination of the best global and local positions.

Fig. 3 shows the above-mentioned procedure graphically.

To apply the hybrid algorithm named ACO-SA on the problem the following steps should be repeated:

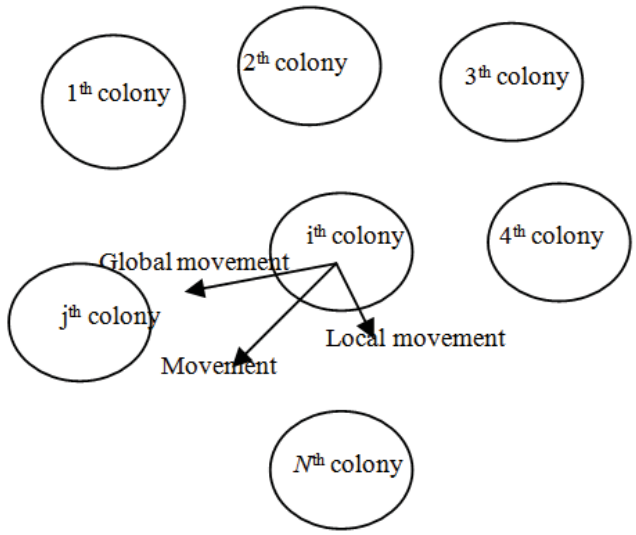

Fig. 3: Determination of the movement direction for colonies

Step1. Generate an Initial Population:

An initial population is randomly generated as follows:

$$Population = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_N \end{bmatrix} \tag{14}$$

$$X_i = [\overline{Tap}, \overline{Q_G}, \overline{U_C}, \overline{P_G}],$$

where $Center_j$ is the j^{th} cluster center for the i^{th} individual. X_i is the position of the i^{th} individual. d is the dimension of each cluster center. $x_i^{\max}$ and $x_i^{\min}$ (each feature of center) are the maximum and minimum value of each point belonging to the j^{th} cluster center, respectively.

Step2. Generate Initial Trail Intensity:

At initialization phase, it is assumed that the trail intensity between each pair of colonies is the same and is generated as follows:

$$Trail\_Intensity = [\tau_{ij}]$$
$$\tau_{ij} = \tau_0 \tag{15}$$

where τ_{ij} and τ_0 are the trial intensity between the i^{th} and j^{th} ants and the initial trial intensity, respectively.

3. Determination of the next path

Assume that the i^{th} colony wants to determine its next position. As mentioned before, the movement direction of each colony is a linear combination of the best global and local positions, which can be selected as:

Selection of the Best Global Position:

The best global position (X_{Global}) is found based on equations (14) and (15). Since L_{ij}, called desirability factor, is not known in the clustering problem, we can define its inverse as follows:

$$1/L_{ij} = \phi_{Gij} = f(X_i) - f(X_j); \quad j \neq i \tag{16}$$

$f(X_i)$ and $f(X_j)$ are the objective function values of the clustering problem for the i^{th} and j^{th} colonies. The transition probabilities between the i^{th} colony and the rest of the colonies are defined as

$$P_{Gij} = \frac{(\phi_{Gij})^{\gamma_1}(\tau_{Gij})^{\gamma_2}}{(\sum_{\substack{j=1 \\ j\neq i}}^{N}(\phi_{Gij})^{\gamma_1}(\tau_{Gij})^{\gamma_2})}, \quad j = 1,2,\ldots,N; \quad i \neq j \tag{17}$$

The cumulative probabilities for colonies are calculated based on the calculated transition probabilities. The best global position is selected by the roulette wheel. The global trail intensities are updated as follows:

$$\Delta\tau_{Gij} = P_{Gij}$$
$$\tau_{Gij}(k+1) = \rho\tau_{Gij}(k) + \Delta\tau_{Gij} \tag{18}$$

***Applying the De Algorithm to Find the Best Local Position*:**

Differential evolution (DE) is a stochastic search algorithm that was originally motivated by the mechanisms of natural selection, invented by Price and Storn in 1995. DE is a simple yet powerful heuristic method for solving optimization problems with non-linear, non-smooth objective functions, since it does not require derivative information.

This technique combines simple arithmetic operators with the classical events of crossover, mutation and selection to evolve from randomly generated initial population to final individual solution. The key idea behind DE is a scheme for generating trial parameter vectors. Mutation and crossover are used to generate new vectors, and selection then determines which of the vectors will survive the next generation.

To apply the DE algorithm on the ED problem the following steps should be repeated:

Step 1: read the input data
Step 2: generate an initial population randomly
Step 3: evaluate fitness function
Step 4: crossover operation
Step 5: mutation operation
Step 6: termination criteria

Determination of the next Position:

After selecting the best local and global positions, the next position is determined as follows:

$$X_i(k+1) = X_i(k) + rand()*(X_{Local} - X_i(k)) + rand()*(X_{Global} - X_i(k)) \tag{19}$$

It must be noted that in the new position the constraint must be completely satisfied.

Step4. Check of Convergence:

After that all colonies have found their next positions, the convergence condition is checked as below:

$$\sqrt{\sum_{i=1}^{N}\left|X_i^{k+1} - X_i^{k}\right|^2} < \varepsilon \tag{20}$$

where $k+1$ is the current iteration.

If the convergence condition is satisfied, the task is complete and if not, the process must be repeated from step 3. Fig.4 shows the complete flowchart of the process.

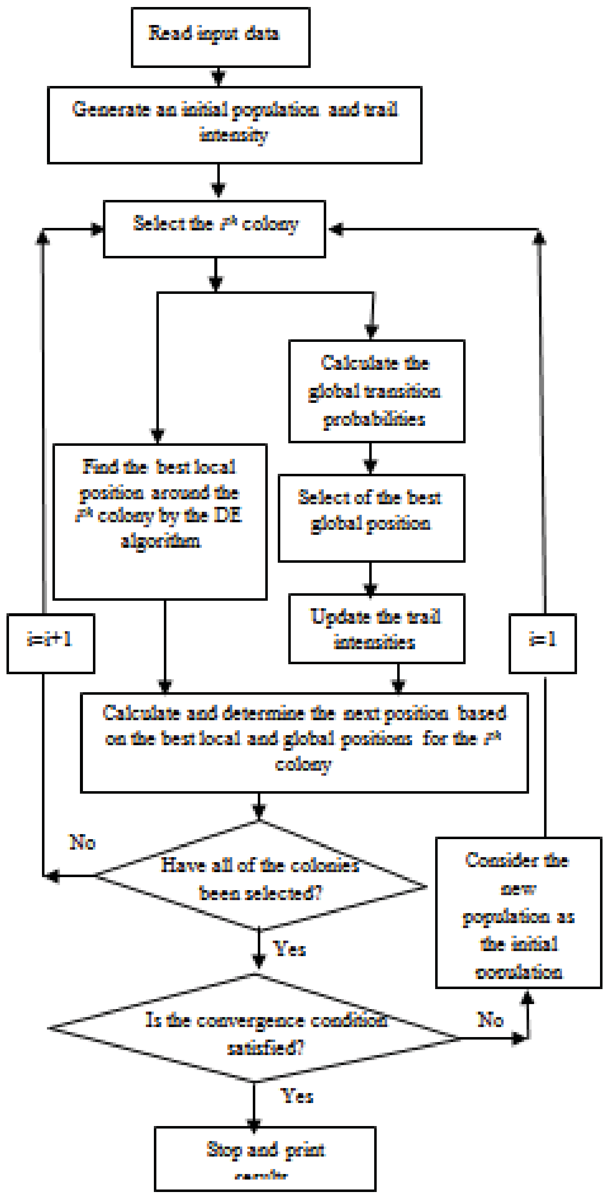

Fig. 4: The flowchart of the ACO-DE algorithm

Simulation Results:

This part, the daily Volt/Var control in distribution networks considering DERs is tested on a 70-bus distribution system. It is assumed that daily energy price variations and daily load variations are changed as shown in Figs. 5 and 6.

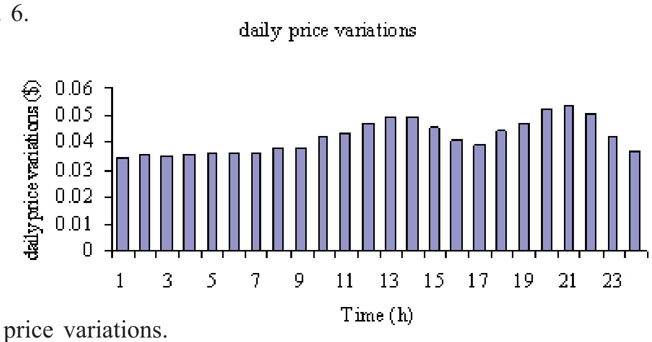

Fig. 5: Daily energy price variations.

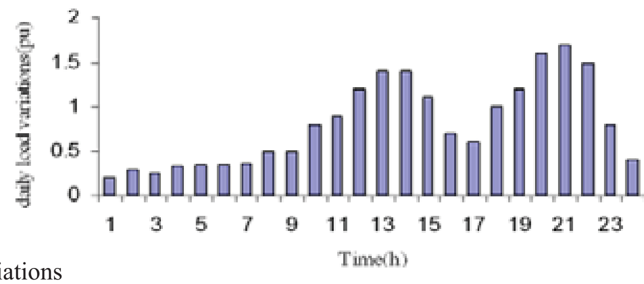

Fig. 6: Daily load variations

Fig. 7 shows a single-line diagram of this network whose associated specifications are presented in (Carvalho, P.M.S., 2008). It is assumed that there are 8 DERs whose specifications are given in Table 1. Capacitors characteristics are in Table 2, respectively.

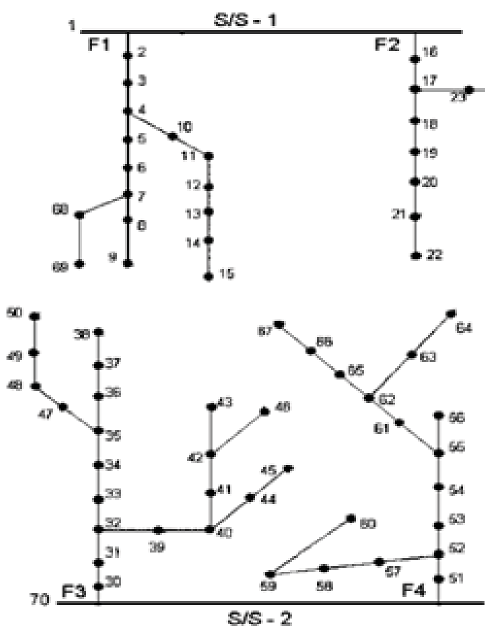

Fig. 7: A single line diagram of 70-bus test system

Table 1: Characteristics of Ddistributed Generators

	Capcity (Kw)	Max Reactive power(kVar)	Min Reactive power(kVar)	Price($/kWh)	location
G1	500	400	-250	0.04	8
G2	500	400	-250	0.05	14
G3	500	400	-250	0.05	21
G4	500	400	-250	0.04	27
G5	500	400	-250	0.05	38
G6	500	400	-250	0.04	42
G7	500	400	-250	0.05	59
G8	500	400	-250	0.04	62

In this paper, it is supposed that the maximum numbers of switching operations for capacitors along the feeder and at the substation bus (main station) are 1 and 3. Also, it is assumed that the transformers and VRs have 21 tap positions ([-10, -9… 0, 1, 2…10]) and the MADOT of them in a day is 30. They can change voltage from –5% to +5%. The number of variables is 312 (number of capacitors × 24+ number of DERs × 2×24+ number of transformers × 24 + number of voltage regulators × 24).

Table 3 presents a comparison among the results of ACO-DE, Particle Swarm Optimization (PSO) (Niknam, T., 2005; Madureira, A.G., 2009), Tabu Search (TS)(Niknam, T., 2005; Viawan, F.A. and D. Karlsson, 2008), Differential Evolution (DE)) (Niknam, T., 2005; Su, C.L., 2009) and Genetic Algorithm) (Niknam, T., 2005; Senjyu, T., 2008) for 300 random tails.

Fig. 8 depicts the convergence characteristic of the ACO for the best solution.

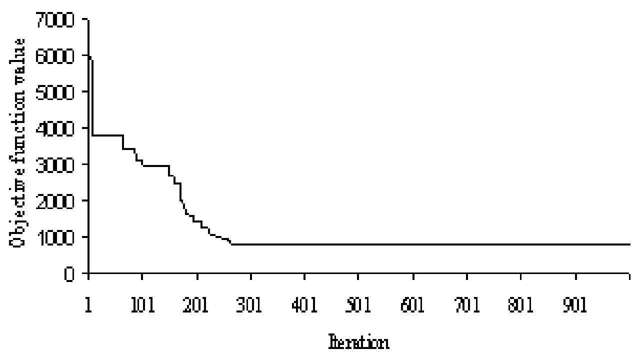

Fig. 8: Convergence characteristics of the ACO-DE for the best solutions

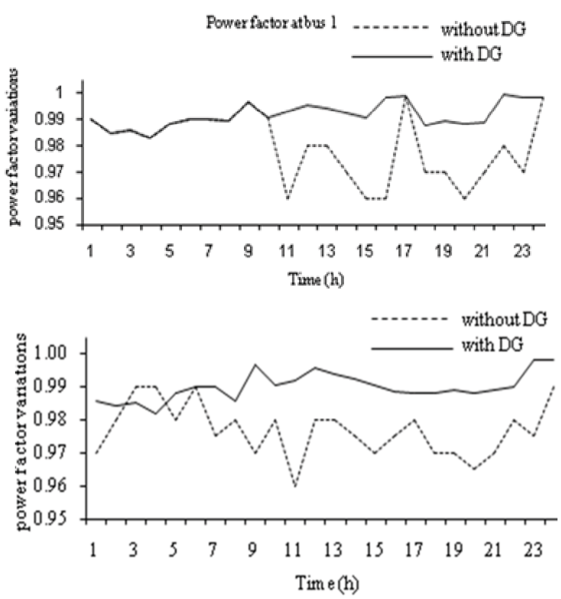

Fig. 9: Power factor variations at substation bus over a day

A substation power factor variation for two cases (with DER and without DER) is shown in Fig. 9. The voltage changes of some buses are shown in Figs. 10 , 11 and 12.

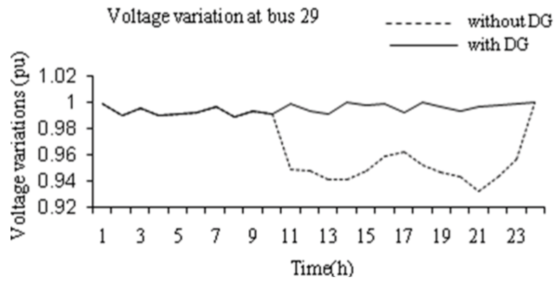

Fig. 10: Voltage variations of bus29 over a day

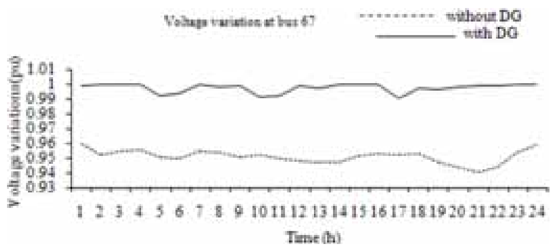

Fig. 11: Voltage variations of bus 67 over a day

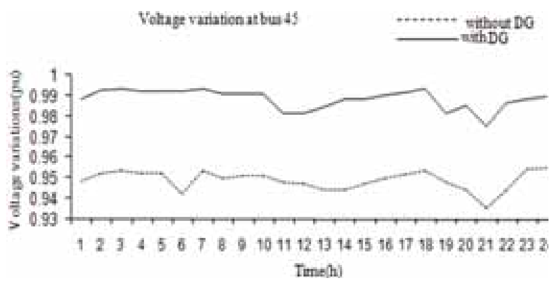

Fig. 12: Voltage variations of bus45 over a day

Table 2: Charcteristics of Capacitors

Capacitor Number	Location (bus No)	Size (kVar)
C_{Sub1}	1	600
C_{Sub2}	70	600
C_1	5	500
C_2	28	500
C_3	35	500
C_4	55	500

Table 3: Comparison of Average and Standard Deviation for 300 Trails

Method	Average	Standard Deviation	Worst solution	Best solution
ACO-DE	1032.23	31.6453	1065.86	1004.34
PSO	1450.77	205.122	1657.62	1232.42
TS	1400.92	200.64	1627.71	1222.48
DE	1332.96	102.12	1467.47	1228.92
GA	1450.92	215.689	1662.71	1238.9

Table 4 represents the simulation results in terms of the number of capacitors' allowable switching operations.

Tables 5 and 6 show the reactive and real power components of the DG units, as commanded by the algorithm.

Table 4: Influence of Maximum Allowable Switching Operation of Capacitors

Maximum number of allowable switching operation	The proposed in paper	Infinite
Energy Losses (kWh) (with DG)	2510	2677
Energy Losses (kWh) (without DG)	4093	3283

Table 5: Active Power Fo Dg Units

Time (h)	Pgl (kw)	Pg2 (kw)	Pg3 (kw)	Pg4 (kw)	Pg5 (kw)	Pg6 (kw)	Pg7 (kw)	Pg8 (kw)
1	0	0	0	0	0	500	0	500
2	0	0	0	0	0	500	0	500
3	0	0	0	0	0	500	0	500
5	0	0	0	0	0	500	0	500
6	0	0	0	0	0	500	0	500
7	0	0	0	0	0	500	0	500
8	0	0	0	0	0	500	0	500
9	0	0	0	0	0	500	0	500
10	500	0	500	0	260	500	260	500
11	500	0	500	0	420	500	420	500
12	500	0	500	0	500	500	500	500
13	500	200	500	200	500	500	500	500
14	500	200	500	200	500	500	500	500
15	500	0	500	0	500	500	500	500
16	500	0	500	0	0	500	0	500
17	500	0	500	0	0	500	0	500
18	500	0	500	0	500	500	500	500
19	500	0	500	350	500	500	500	500
20	500	350	500	350	500	500	500	500
21	500	350	500	350	500	500	500	500
22	500	350	500	350	500	500	500	500
23	500	0	500	0	250	500	250	500
24	0	0	0	0	0	500	0	500

Table 6: Reactor Power of Dg Units

Time (h)	Qgl (kVar)	Qgl^2 (kVar)	Qgl^3 (kVar)	Qgl^4 (kVar)	Qgl^5 (kVar)	Qgl^6 (kVar)	Qgl^7 (kVar)	Qgl^8 (kVar)
1	-100	-100	-100	-100	-100	-100	-100	-100
2	-100	-100	-100	-100	-100	-100	-100	-100
3	-100	-100	-100	-100	-100	-100	-100	-100
4	-100	-100	-100	-100	-100	-100	-100	-100
5	-100	-100	-100	-100	-100	-100	-100	-100
6	-100	-100	-100	-100	-100	-100	-100	-100
7	-100	-100	-100	-100	-100	-100	-100	-100
8	-100	-100	-100	-100	-100	-100	-100	-100
9	-100	-100	-100	-100	-100	-100	-100	-100
10	400	400	400	400	400	400	400	400
11	400	400	400	400	400	400	400	400
12	400	400	400	400	400	400	400	400
13	400	400	400	400	400	400	400	400
14	400	400	400	400	400	400	400	400
15	400	400	400	400	400	400	400	400
16	400	400	400	400	400	400	400	400
17	400	400	400	400	400	400	400	400
18	400	400	400	400	400	400	400	400
19	400	400	400	400	400	400	400	400
20	400	400	400	400	400	400	400	400
21	400	400	400	400	400	400	400	400
22	400	400	400	400	400	400	400	400
23	371	-100	371	-100	185	371	185	371
24	-100	-100	-100	-100	-100	-100	-100	-100

Discussion:

In this section, with reference to tables and figures presented in the previous section, a discussion can be summarized as follows:

1. The ACO-DE method is very precise. In other words, not only does this method reach a much better optimal solution in comparison with others, but also the standard deviation for different trails is very small (Table 3).
2. Since most of DERs have private ownership, the cost of active power generation can be used as an encouraging signal.

3. The voltage magnitude at each bus is in the desired limits (Figs. 10, 11 and 12).
4. In the first case study, summation of electrical energy losses is 2540 kWh whole in case 2 it is 4090 kWh. Under the proper control on DERs, electrical energy losses are much less than the other case. On the other hand, it can be concluded that the system performance can be improved under proper control (Tables 4).
5. The power factor at the substation bus is in the desired limits for the whole day (Fig.9).
6. The electric energy losses in the first case have much lower sensitivity to changes in capacitor switching operation (Table 4). In other words, when DERs are controllable, the daily Volt/Var control problem can be solved for each step of load levels independently. This means that the convergence time decreases (Table 4).
7. Distributed generators have much better performance and time response than other sources of reactive power generation like capacitors. Thus system performance can be improved considering proper factors to control them.
8. Tables 5 and 6 indicate that, to minimize the objective function, the active and reactive power components of all DERs are changed during the day. The active powers of DG1, DG2, DG3, DG4, DG5 and DG7 are zero in some hours. The reason for this can be explained from the data of Table I; these generators have high price compared to substation price in the mention hours.

Conclusion:

As pointed in the previous sections, issues such as environmental pollution, restructuring in electrical industry and technology advancement have resulted in an increase in the usage of distributed energy resources which most of the time connect to the distribution networks. Therefore, with increase in connection of these generators to the distribution networks, it is necessary to study the effects of these generators on distribution systems and define proper signals to control them. In this paper, a new cost-based compensation methodology has been used as a proper signal to encourage DERs in active and reactive power generation. The simulation results show that the defined factor has caused more reduction in the total electrical energy losses in the system. Besides the above objective function, a method, based on the ant colony algorithm and DE algorithm, has been applied to solve the optimization problem of voltage and reactive power control. The simulation results indicate that this optimization method is very precise and converges very rapidly so that it can be used in practical systems.

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