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Multiobjective daily Volt/VAr control in distribution systems with distributed generation using binary ant colony optimization

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Abstract: This paper presents a multiobjective daily voltage and reactive power control (Volt/VAr) in radial distribution systems, including distributed generation units. The main purpose is to determine optimum dispatch schedules for on-load tap changer (OLTC) settings at substations, substation-switched capacitors, and feeder-switched capacitors based on the day-ahead load forecast. The objectives are selected to minimize the voltage deviation on the secondary bus of the main transformer, total electrical energy losses, the number of OLTCs, and capacitor operation and voltage fluctuations in distribution systems for the next day. Since this model is the weighted sum of individual objective functions, an analytic hierarchy process is adopted to determine the weights. In order to simplify the control actions for OLTC at substations, a time interval-based control strategy is used for decomposition of a daily load forecast into several sequential load levels. A binary ant colony optimization (BACO) method is used to solve the daily voltage and reactive control, which is a nonlinear mixed-integer problem. To illustrate the effectiveness of the proposed method, the Volt/VAr control is performed in IEEE 33-bus and 69-bus distribution systems and its performance is compared with the genetic, hybrid binary genetic, and particle swarm optimization algorithms. The simulation results verify that the BACO algorithm gives better performances than other algorithms.

Key words: Distributed generators, binary ant colony optimization, multiobjective, reactive power and voltage control

1. Introduction

Volt/VAr control in distribution systems involves proper coordination among the on-load tap changer (OLTC) and all of the switched shunt capacitors in the distribution system to obtain an optimum voltage profile and optimum reactive power flows in the system according to the objective function and operating constraints [1].

The voltage and reactive power equipment in distribution systems are mostly operated based on an assumption that the voltage decreases along the feeder. On the other hand, the connection of distributed generation (DG) will fundamentally alter the feeder voltage profiles, which will obviously affect the voltage control in distribution systems. Recently, concerns about the global environment and energy security have raised expectations for distributed generators, such as wind-power generation, photovoltaic generation, fuel cells, and micro-gas turbines. Today's improvements in the performance and efficiency of DG are encouraging an increase in amount of DG installed into electric power systems. The installation of DG into power systems has some merits, such as the reduction of transmission and distribution losses. On the other hand, it also brings some technical problems such as the occurrence of over-voltages or under-voltages on distribution feeders, injection of current harmonics, or islanding operation of DG. Therefore, it is essential to consider the impact of DGs

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on power systems, especially on distribution networks, because the configuration of a distribution network is generally radial and the X/R ratio of distribution lines is small.

Nowadays, research on the Volt/VAr control for distribution systems can be divided into 2 categories: offline setting control and real-time control. Research in offline setting control [2–4] aims to find dispatch schedules for switching capacitors and OLTC settings at substations for the day ahead according to optimization calculations based on load forecasts for the day ahead, while research for real-time control aims to control the aforementioned devices based on real-time measurements and experiences. The second category of control requires a higher level of distribution system automation and more hardware and software support [5]. Until recently, the majority of distribution systems did not reach such standards. Furthermore, it is very difficult for real-time control to consider the overall load change as well as the constraints of the maximum allowable switching operations for a number of Volt/VAr control devices.

Recently, multiobjective optimization approaches for Volt/VAr control have become more attractive [6–14]. However, the focus has been concentrated on power losses and voltage deviation. Relatively little effort has been directly involved with the number of OLTCs and capacitor operations. So far, various mathematical optimization algorithms, such as linear programming and gradient-based algorithms, in Volt/VAr control problems have been applied [15–17]. However, the optimal dispatch of all Volt/VAr control devices is a multiphase decision-making problem. For each hour, it is a discrete and nonlinear problem. Therefore, using traditional mathematical methods can be very complex and entails a heavy computational burden.

In recent years, a wide variety of evolutionary algorithms [6–12], such as the genetic algorithm, particle swarm optimization, and honey bee mating optimization, have been used for the Volt/VAr control problem. The ant colony optimization (ACO) algorithm is one kind of heuristic biological modeling method to solve combinatorial optimization problems. The ACO method has been researched in various aspects and successfully applied to various optimization problems. The conventional ACO shows reasonable performance for small problems with moderate dimensions and searching space. However, it is not suitable for large-scale problems such as Volt/VAr control problems, because the size of the pheromone matrix grows exponentially along with the problem size [18]. In this study, a new algorithm named binary ant colony optimization (BACO) is proposed and implemented for Volt/VAr control problems to resolve the conventional ACO limitations.

An ACO to determine the active and reactive power values of DGs, the tap positions of transformers, and reactive power values of capacitors was proposed in [7]. A time interval–based control strategy to reduce switching operations for OLTCs at substations was adopted in [3]. In [8], Niknam et al. proposed a cost-based compensation methodology for daily Volt/VAr control in distribution networks, including DGs. A new optimization algorithm based on a chaotic improved honey bee mating optimization is proposed to determine the active power values of DGs, reactive power values of capacitors, and tap positions of transformers for the next days in [9]. In [10], a method to optimize the reactive power flow with regard to multiple objectives while maintaining system voltage security across a time domain was proposed. Liang et al. [11] presented a fuzzy optimization approach for solving Volt/VAr control problems in a distribution system with uncertainties. Wind turbines were considered in the study distribution system in [11]. An improved multiobjective genetic algorithm (SPEA2) using fuzzy logic was presented to solve Volt/VAr control for radial distribution feeders in planning issues, by means of the application of automatic voltage regulator banks and capacitors proposed in [13]. An approach for the control of distribution voltage considering DGs with the coordination of distributed installations, such as the load ratio control transformer, step voltage regulator, shunt reactor, shunt capacitor, and static VAr compensator, was proposed in [15]. In [1], Viawan et al. presented the impact of synchronous machine-based DG to the available Volt/VAr control and they also proposed a proper coordination strategy among DG and other traditional Volt/VAr control equipment.

In this paper, the Volt/VAr control is formulated as a multiobjective optimization problem. The objectives consist of the voltage deviation on the secondary bus of the main transformer, the total electrical energy losses, the number of OLTC and capacitor operations, and the voltage fluctuation in the distribution systems. The optimal dispatch of all Volt/VAr control devices is a multiphase decision-making problem. For each hour, it is a discrete and nonlinear problem. Therefore, in this paper, a method based on the analytic hierarchy process (AHP) strategy and the BACO algorithm is employed that uses a special encoding method to avoid such problems. The main contributions of this paper can be illustrated as follows: 1) present a new multiobjective approach for the daily Volt/VAr control in distribution networks considering DGs, and 2) propose a new BACO algorithm to solve the daily Volt/VAr control. To illustrate the effectiveness of the proposed method, the Volt/VAr control is performed in IEEE 33-bus and 69-bus distribution systems and its performance is compared with the genetic algorithm (GA) and the hybrid binary GA and particle swarm optimization (HBGAPSO) algorithms. Simulation results show that the BACO algorithm gives better performances than the other algorithms and the optimal dispatch schedule for the OLTC settings and capacitor switching operation can be found effectively.

2. Problem formulation

With the development of a distribution management system, loads along each feeder bus and substation secondary bus can be obtained for the upcoming day by employing short-term load forecasting techniques [4].

Generally, in a distribution system, to compensate for the voltage drop over the transformer and upstream lines, an OLTC is installed. Shunt capacitors inject reactive power to the system to compensate for the reactive power demand and thereby boost the voltage.

The objective of the Volt/VAr control considering DG is to determine a proper dispatching schedule of the OLTC tap position and shunt capacitor status for the day ahead. Meanwhile, the voltage deviation on the secondary bus of the main transformer, the total electrical energy losses, the number of OLTC and capacitor operations, and the voltage fluctuations in the distribution systems can be minimized. To do this, the study period is divided into 24 time intervals and the Volt/VAr control problem in a distribution system considering DG can be formulated as explained below.

2.1. Objective functions

In this paper, we set up the objective function considering 5 factors, which are the voltage deviation on the secondary bus of the main transformer, the total electrical energy losses, the number of OLTC and capacitor operations, and the voltage fluctuations in the distribution systems. By weighting the addition among these 5 factors, the objective function can be described as follows:

$$\min w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 + w_5 f_5, \tag{1}$$

where $\mathrm{w}_i,\ i \in 1, \ldots, 5\}$ are the weighting factors and f_i are the factors considered in this paper, which are described below.

2.1.1. Total electrical energy losses

The first objective is to minimize the total active power losses for the day ahead. The load profile is divided by a 1-h interval between 2 subsequent stages:

$$\text{minimize } f_1 = \sum_{i=1}^{N} P_{Loss,i}, \tag{2}$$

where $P_{Loss,i}$ is the total system losses at time i and N is the number of stages in a day, which is 24 for a $1-h$ interval between i and i + 1.

2.1.2. Voltage deviation on the secondary bus

The voltage deviation on the secondary bus of the main transformer is calculated as:

$$\text{minimize } f_2 = \sum_{i=1}^{N} |\Delta V_{2,i}|, \tag{3}$$

where $\Delta V_{2,i} = \Delta V_{2,i} - 1$ is the voltage deviation on the secondary bus of the main transformer at time i.

2.1.3. Voltage violation

To avoid the bus voltages reaching their maximum limits, the voltage violation is taken as the third objective function, which is:

$$\text{minimize } f_3 = \frac{1}{N_L} \sum_{h=1}^{N_L} \sum_{i=1}^{N} |V_{h,i} - V_{h,i-1}|, \tag{4}$$

where f_3 is the average of the steady-state voltage fluctuation, $V_{h,i}$ is the voltage at bus-h at time i, and N_L is the total number of system load buses.

2.1.4. Daily number of OLTC operations

The OLTCs are moved quite often, resulting in a reduction of the OLTC life expectancy and higher repairing costs. Hence, the daily number of OLTC operations is considered as the fourth objective function:

$$\text{minimize } f_4 = \sum_{i=1}^{N} |TAP_i - TAP_{i-1}|, \tag{5}$$

where f_4 is the daily number of OLTC operations and TAP_i is the OLTC tap position at time i.

2.1.5. Daily number of switching operations for shunt capacitors

The daily number of switching operations for both substation capacitors (the shunt capacitors installed at the substation secondary bus) and feeder capacitors (the shunt capacitors located somewhere along the feeder) is considered as the fifth objective function:

$$\text{minimize } f_5 = \sum_{k=1}^{C_T} \sum_{i=1}^{N} (C_{k,i} \oplus C_{K,i-1}), \tag{6}$$

where $C_{k,i}$ is the status of capacitor k (on or off) at time i, C_T is the total number of shunt capacitors that are installed in the distribution system, and $\oplus$ is the exclusive OR operation.

2.2. Constraints

The objective function is subject to standard power balancing equality constraints as well as the following additional inequality constraints:

Bus voltage magnitude:

$$V_{\min}<V_{h,i}<V_{\max}. \tag{7}$$

Line flow limit:

$$S_{TX,i}\leq S_{TX,rat}. \tag{8}$$

Daily number of OLTC operations limit:

$$\sum_{i=1}^{N}|TAP_i-TAP_{i-1}|\leq TAP_{\max}. \tag{9}$$

Daily number of switching operations for shunt capacitors limit:

$$\sum_{i=1}^{N}(C_{k,i}\oplus C_{K,i-1})\leq CM_k. \tag{10}$$

Here, $S_{TX,i}$ is the apparent power flow on the substation transformer at time i, $S_{TX,rat}$ is the substation transformer rating, $V_{\min}$ is the minimum allowed voltage, $V_{\max}$ is the maximum allowed voltage, $TAP_{\max}$ is the maximum switching operation for the OLTC, and CM_k is the maximum switching operation for capacitor k.

3. Weight value determination based on AHP method

The AHP is a systematic multicriteria decision-making method developed by Saaty in 1970 [19], which has been widely used to assess complex systems or projects. It is helpful for decision makers in that it simplifies the complicated determination of precise weighted factors to a series of pair-wise qualitative comparisons of criteria in a systematic way, such that the best decision can be made by setting priorities for all of the possible solutions. The values of all of the objective functions are transformed into the same range: [0,1]. The pair-wise comparison judgment matrix for the 5 objective functions for this paper is shown in Table 1. The weighted factor vector can be obtained as: W = $[0.5912, 0.1650, 0.1317, 0.0727, 0.0394]^T$.

Table 1. Pair-wise comparison judgment matrix.

Objective function	f_1	f_2	f_3	f_4	f_5
f_1	1	6	6	8	9
f_2	0.1667	1	2	3	4
f_3	0.1667	0.5	1	3	4
f_4	0.125	0.333	0.333	1	3
f_5	0.1111	0.25	0.25	0.333	1

4. Ant colony optimization

The ACO algorithm was inspired by the action of biological ants. Therefore, describing the behavior of the biological ants can help understand how artificial ants solve an optimization problem by transiting from node to node. Real ants lay an aromatic substance, known as pheromone, on the earth when they move through a place. Each ant chooses its path with respect to the consistency of the pheromone that is laid along the way. Indeed, ants prefer to go through a path with a large amount of pheromone on it. The path will be marked again when other ants go along it. Hence, this path will have a high probability to be chosen. In other words, the best way has more intensive pheromone and a higher probability to be chosen [20,21].

The artificial ants have the same action as biological ants. They live in a discrete space. In addition, they move from node to node according to their previous actions, which is stored in a memory with a special data structure [22]. The pheromone consistencies of all of the paths are updated only after the ant has finished its tour from the first node to the last node. Every artificial ant has a constant amount of pheromone stored in it when the ant proceeds from the first node. The stored pheromone will be evenly distributed on the path after the artificial ants have finished their tour. The amount of pheromone will be high if the artificial ants finish their tour with a good path and vice versa. The pheromone of the routes progressively decreases by evaporation in order to avoid the artificial ants getting stuck in the local optima solution [23].

4.1. Binary ant colony optimization

A continuous optimization problem can be described as:

$$\min J = f(x), \tag{11}$$

$$x_{\min} \leq x \leq x_{\max}; x = (x_1, x_2, \ldots, x_n) \in R^n.$$

The feasible regions of all of the variables in x should be represented by binary strings in order to construct a search space before the BACO begins. Every variable x_i in the candidate solution $\{x_1, x_2, \ldots, x_n)$ is expressed by an N-bit–long binary string $\{b_N, b_{N-1}, \ldots, b_1\}$, where $b_j \in \{0,1\}$, j = 1, 2,..., N, and N is the string length. The best solution can be considered as a problem of searching the best path in a directed graph, as shown in Figure 1. The nodes of the graph consist of 0 and 1, which are the state candidates of every bit. The graph arcs connect possible state transition routes between 2 adjoining bits.

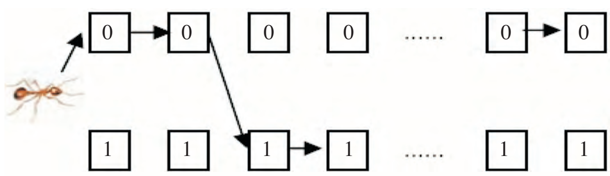

Figure 1. Feasible paths of the BACO.

In each iteration, every ant travels to all of the N nodes of the n variables to construct a solution candidate. Its trace generates n binary strings, and the k*th* binary string can be decoded and mapped into X_k by converting it to a decimal number. Next, a solution candidate x = $(x_l, \ldots, x_k, \ldots, x_n)$ is constructed.

Let τ_{ab}^{ki} represent the pheromone on the arc from state a to state b at the j*th* bit of the variable x_k, with a, b $\in \{0, 1\}$. As shown in Figure 1, there are 2 arcs leading to the next vertex for every bit. An ant selects its route according to the pheromone distribution on both arcs. It moves towards the next node according to the probability distribution given by Eq. (12):

$$p_{ab}^{ki}\left(t\right) = \frac{\tau_{ab}^{ki}(t)}{\sum_{s\in\{0,1\}}\tau_{as}^{ki}(t)}. \tag{12}$$

After time period's n, the ant completes one circle, and the information on every routine will adjust as follows:

$$\tau_{ab}^{ki}\left(t+1\right) = \rho\tau_{ab}^{ki}\left(t\right) + \Delta\tau_{ab}^{k}(t), \tag{13}$$

where ρ represents the durability of the track ($0 \leq \rho \leq 1$) and $\Delta\tau_{ab}^{k}(t)$ is the incremental pheromone, which can be computed by [23]:

$$\Delta\tau_{ab}^{k}\left(t\right) = \begin{cases} \frac{1}{f(s^{ib})} & \text{if the } arc \text{ from } a \text{ to } b \text{ is in the trace of} s^{ib} \\ 0 & \text{else} \end{cases}, \tag{14}$$

where s^{ib} is the iteration-best and f(s^{ib}) is the solution cost of s^{ib}.

Such a strategy may lead to a stagnation situation in which all of the ants follow the same tour, because of the excessive growth of the pheromone trails on the arcs of a good, although suboptimal, tour. To counteract this effect, a modification applied in this paper is introduced by the MAX-MIN ant system (MMAS), which limits the possible range of the pheromone trail values to the interval $[\tau_{\min}, \tau_{\max}]$ [24]. In the MMAS, lower and upper limits $t_{\min}$ and $t_{\max}$ on the possible pheromone values on any arc are imposed in order to avoid search stagnation. The upper and lower pheromone trail limit on any arc is bounded by [24]:

$$\tau_{\max} = \frac{1}{(1-\rho)*f_m},$$

$$\tau_{\min} = \frac{\tau_{\max}(1-\sqrt[n]{0.05})}{\left(\frac{n}{2}-1\right)\sqrt[n]{0.05}}. \tag{15}$$

The steps of the BACO algorithm are as follows:

Step 1: Initialize parameters.

For the BACO proposed in this paper, parameter choosing is researched so as to get the best effect. It is very important to select the parameter of the BACO and different parameters will have different results. At the start of the algorithm, the initial pheromone trails τ_0 are set to an estimate of the upper pheromone trail limit.

Step 2: Encoding design.

Binary encoding is adopted. The dimension of the optimization function decides the number of the routines that ants traverse in every circle. The first routine that an ant has traversed is the first variable of the corresponding function, and so is the second routine, by analogy.

Step 3: Compute transition probability of each ant and select next route.

The node is selected by ant k according to each element's transition probability and is defined as in Eq. (12).

Step 4: Fitness evaluation.

In this step, after all of the ants have completed their tours, the control variable x is computed and the fitness evaluation is performed.

Step 5: Apply the updating rule.

The pheromone amount is calculated as in Eq. (13).

Step 6: Pheromone trail limits.

Lower and upper limits $\tau_{\min}$ and $\tau_{\max}$ on the possible pheromone values on any arc are imposed in order to avoid search stagnation, as is described in Eq. (15).

Step 7: End condition.

The algorithms stop the iteration when a maximum number of iterations have been performed; otherwise, repeat Step 3. The best path selected between all of the iterations engages the optimal scheduling solution.

The flow chart of the improved ant colony algorithm is shown in Figure 2.

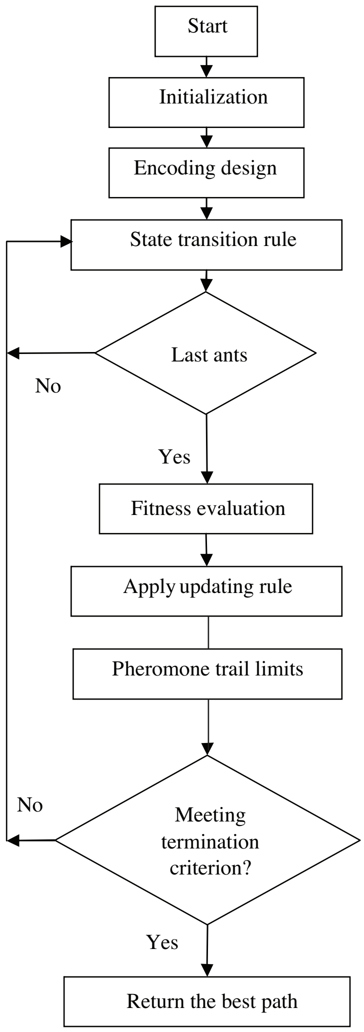

Figure 2. Flowchart of the BACO.

4.2. Encoding

4.2.1. Shunt capacitors

Feeder capacitors are allowed, at most, to switch 3 times in a day. If for any capacitor 24 bits are considered, where each bit represents the capacitor's on/off status in the hour, then the total number of bits of the problem is very high and the time to achieve an optimal solution increases. Hence, in this paper, for feeder capacitors, only the time of the capacitor switches is considered. Since each day is 24 h for each switch operation, 5 bits are considered. Therefore, the number of bits intended for encoding the feeder capacitors is equal to 5 $\times$ 3, which is a value not greater than 24. If this number is multiplied by the total number of feeder capacitors, the genome length will be significant, and therefore the search space needed to achieve an optimal solution will decrease.

The maximum number of switches that substation capacitors are allowed each day is 6. Hence, each capacitor holds one segment in the genome. The length of the segment is 24 bits if the value of the i*th* bit is 0; it denotes that the capacitor is off at time i.

4.2.2. OLTC

It is difficult to specify the controlling parameters when applying automated techniques to control OLTCs at a substation level. It should also be noted that, because of the probabilistic nature of load forecasting, it could be construed as inaccurate to determine a dispatch schedule of the OLTC settings based only on load forecasting [1,2]. However, to achieve the 24-h optimization of multiobjective reactive power and voltage control requires excessive calculation. Thus, to speed up the calculation process and to simplify the control actions, it is necessary to divide the load curve into several intervals. In each interval, the control actions are performed only once. Hence, in this study, the method described in [4] is applied.

To meet this goal, first, the number of load levels in a day (M) is assumed as a known parameter based on the load forecast and control engineer experience. After that, the BACO algorithm is employed to determine the start and end times of each load level. The fitness function is [4]:

$$Min\left(\sum_{i=1}^{M}\sum_{j=1}^{N_i}\left[\left|(P_{ij}-AVP_i)\right|+\left|(Q_{ij}-AVQ_i)\right|\right]\right), \tag{16}$$

where P_{ij} is the active power of the j*th* load point of the i*th* load level, Q_{ij} is the reactive power of the j*th* load point of the i*th* load level, AVP_i is the average active power of the i*th* load level, and AVQ_i is the average reactive power of the i*th* load level.

The operational characteristic is that the tap position can be different at different load levels and remains constant during each load level.

5. The proposed algorithm for Volt/VAr control

The multiobjective Volt/VAr control problem can be converted into a single-objective optimization by the AHP method. A single-objective optimization problem will easily be solved by the BACO approach. The proposed method based on BACO can offer a best global optimum solution for multiobjective Volt/VAr control problems. A schematic flowchart of the computational procedure is shown in Figure 3 and is described as follows:

Step 1: The input data, including the network configuration, line impedance and status of the distributed generators, loads, transformers and shunt capacitors, forecasted loads, and a specified number of load levels (M), have to be read.

Step 2: Determine the start and end times of each load level based on Section 3.2.

Step 3: Calculate the weighted factors based on the AHP.

Step 4: Apply BACO.

Step 5: Check the stop criterion, usually a sufficiently good fitness value or a maximum number of iterations.

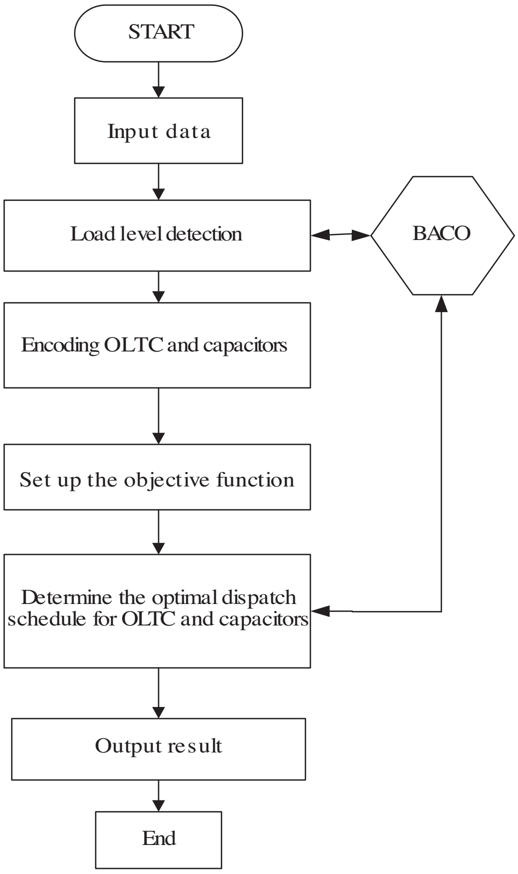

Figure 3. Flowchart of the Volt/VAr control algorithm.

5.1. Simulation results

The BACO method for Volt/VAr control in distribution networks considering DG is applied to the IEEE 33-bus and 69-bus distribution power systems.

5.2. IEEE 33-bus distribution system

The IEEE 33-bus distribution system in Figure 4 is used to demonstrate the effectiveness of the proposed method. The study system has been developed from the distribution system in [25]. The total real power and reactive power loads on this system are 3.72 MW and 2.3 MVAr. The initial real and reactive power losses in the system are 0.211 MW and 0.143 MVAr. Table 2 presents the detailed data of the capacitors used in the network. The impedance of the transformer between nodes 0 and 1 is (0.012 + j0.12) per unit. The OLTC has 17 tap positions ([–8, –9, . . . , 0, 1, 2, . . . , –8]). It can change the voltage from –5% to +5%. The upper and lower limits of the voltage for each bus are 1.05 per unit and 0.95 per unit, respectively. The voltage at the primary bus of a substation is 1.0 per unit. We assume that the loads are constant power loads and all of the loads change during a day according to the load profile shown in Figure 5.

For the case of M = 8, the resulting load profile is shown in Figure 5, where the dashed-dotted lines indicate the boundaries between the load levels.

Table 2. Capacitor data for the IEEE 33-bus distribution system.

Capacitor number	C_1	C_2	C_3	C_4	C_5	C_6
Capacity (kVAr)	300	200	250	300	250	200
Location	1	1	8	13	17	28

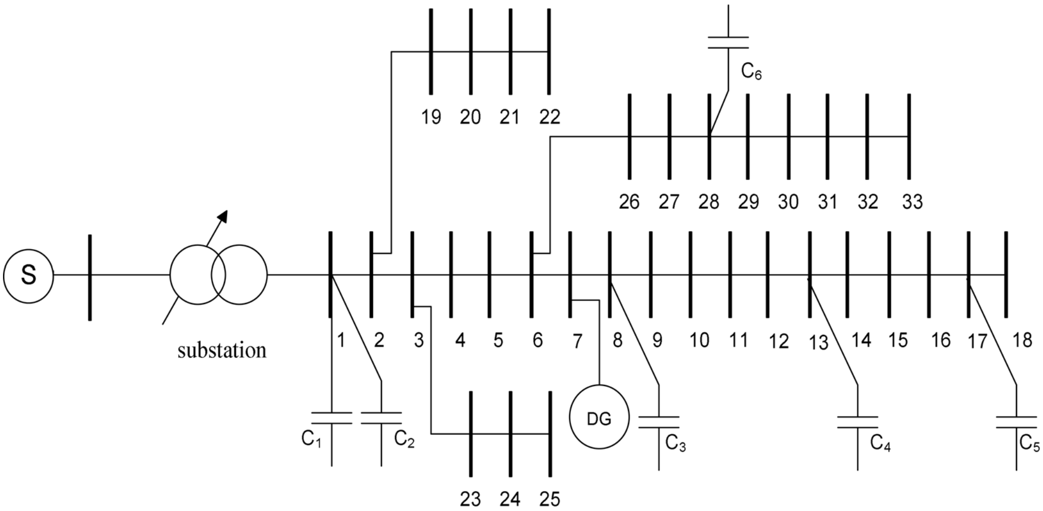

Figure 4. One-line diagram of the IEEE 33-bus distribution system.

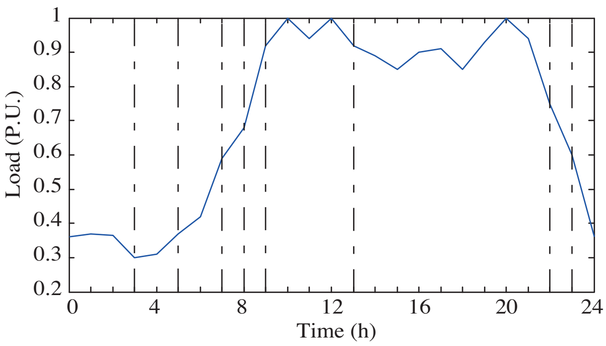

Figure 5. Typical daily load curve.

The DG considered in this paper is a synchronous machine-based DG. The capacity of the DG installed for bus-7 is 1.5 MW. The Volt/VAr control presented in this paper will be tested on 4 different cases: without DG in the system (which will be called Case 1); with uniform DG operation, i.e. synchronous DG operated at constant power at unity power factor (pf) (Case 2); at a constant reactive power output $Q_{DG} = 0.3$ MVAr (Case 3); and at a constant voltage with reactive power limits $Q_{DG,min} = -0.3$ and $Q_{DG,max} = 0.3$ MVAr (Case 4).

Table 3 provides the simulation results carried out on the 33-bus distribution system in the 4 cases. It is shown that when DG exists, the number of capacitor operations decreases. If DG operates at a constant voltage, the number of capacitor operations is minimized. The energy losses shown in Table 3 indicate that DG that generates constant reactive power will give lower losses than DG operating at unity pf. The daily voltage fluctuation in Table 3 shows that the presence of DG decreases the bus voltage fluctuation, where the most significant reduction will be obtained when DG operates at unity pf.

Table 3. The best results for different cases using BACO in the 33-bus distribution system.

	Case 1	Case 2	Case 3	Case 4
f_1 (MWh)	2.1386	1.1073	1.0462	1.1856
f_2 (pu)	0.5910	0.3728	0.3168	0.2316
f_3 (pu)	0.3391	0.2006	0.2125	0.2123
f_4	10	9	9	6
f_5	11	7	8	5

Table 4 shows the daily optimal dispatch results of the OLTCs and capacitors in Case 3 based on the load levels shown in Figure 5. The original position of the tap is 0, and the original status of each capacitor is off (0). The number of switching operations for the OLTCs in the whole day is 9. C_1 and C_2 switch 3 times in a day. The feeder capacitors switch 5 times for the whole day. The voltage at bus 18 is the lowest in the test system. The voltage profile at bus 18, before the control and after using the proposed algorithm in all of the cases, is shown in Figure 6, where it is indicated that in all of the cases, the voltages always stay within the allowed range given by Eq. (7) and the voltage profile at bus 18 is greatly improved. Figure 7 shows the voltage deviation for all of the cases using BACO. A daily real power loss comparison among the 4 cases is shown in Figure 8.

Table 4. Optimal dispatch schedule for day ahead in Case 3.

Hour	TAP	C_1	C_2	C_3	C_4	C_5	C_6
1	0	0	0	0	0	0	1
2	0	0	0	0	0	0	1
3	0	0	0	0	0	0	1
4	0	0	0	0	0	0	1
5	0	0	0	0	0	0	1
6	0	0	0	0	1	0	1
7	0	0	1	1	1	0	1
8	0	0	1	1	1	0	1
9	+3	0	1	1	1	1	1
10	+3	0	1	1	1	1	1
11	+3	1	1	1	1	1	1
12	+3	1	1	1	1	1	1
13	+4	1	1	1	1	1	1
14	+4	1	1	1	1	1	1
15	+4	1	1	1	1	1	1
16	+4	1	1	1	1	1	1
17	+4	1	1	1	1	0	1
18	+4	1	1	1	1	0	1
19	+4	1	1	1	1	0	1
20	+4	1	1	1	1	0	1
21	+4	1	1	1	1	0	1
22	+1	1	0	1	1	0	1
23	–1	1	0	1	1	0	1
24	–1	1	0	1	1	0	1

For comparison purposes, the 3 procedures, the GA, HBGAPSO [26], and BACO algorithm, have been applied to the IEEE 33-bus distribution system with the same conditions and system data. The average results of

100 trials for the total voltage deviation on the secondary bus, the total energy losses, the number of OLTC and capacitor operations, and the voltage fluctuations in the distribution systems obtained using the 3 procedures are presented in Table 5. It is clear that the proposed BACO-based approach outperforms the HBGAPSO and GA techniques. For example, the total energy losses using the GA, HBGAPSO, and BACO algorithms are 1.0488, 1.0476, and 1.0467 MWh, respectively. It is clear that the total energy losses are greatly reduced using the BACO algorithm.

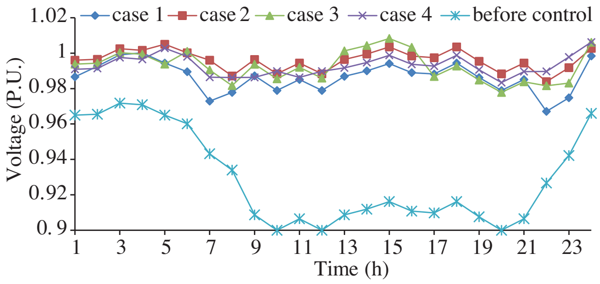

Figure 6. Voltage profile for bus 18 for different cases in the 33-bus IEEE distribution system.

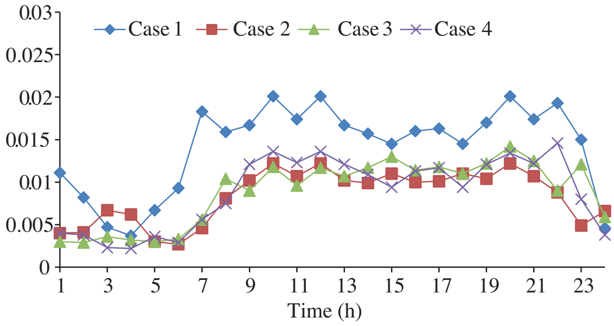

Figure 7. Voltage deviation for 4 cases in the 33-bus IEEE distribution system.

The convergence characteristics of the GA, HBGAPSO, and BACO for the best solution in Case 1 are shown in Figure 9. For the sake of conciseness, Figure 9 shows only the convergence characteristics of the total energy losses' objective function. It can be seen from Figure 9 that the value of the total energy losses using the GA, HBGAPSO, and BACO algorithms converges to the global minimum point after about 95, 80, and 70 iterations, respectively.

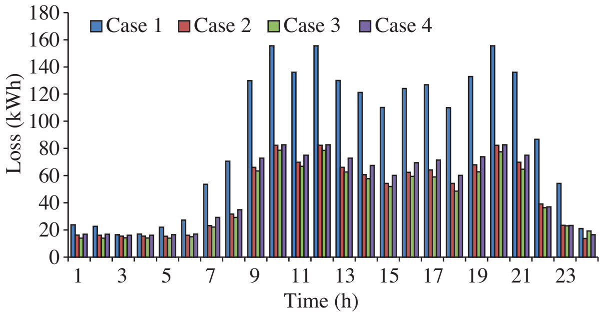

Figure 8. Comparison of daily real power losses in the 33-bus distribution system in 4 cases.

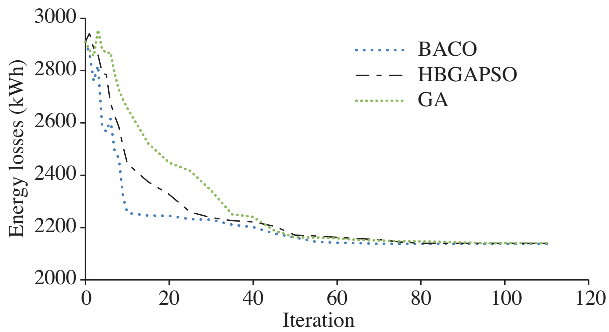

Figure 9. Convergence characteristics of the GA, HB-GAPSO, and BACO for the best solutions in Case 1.

The proposed BACO-based approach was implemented using MATLAB R2008a and the developed software program was executed and implemented on a P4-2.4 GHz personal computer. According to Table 5, the average computing time for the GA, HBGAPSO, and BACO algorithms is 19.6, 16.2, and 14.8 min, respectively. It can be shown that the BACO algorithm has the minimum execution time among the 3 methods.

Table 5. Average results of 100 trials from different optimization procedures: GA, HBGAPSO, and BACO for the 33-bus distribution system.

Method	f_1 (MWh)	f_2(pu)	f_3(pu)	f_4	f_5	Calculation time (min)
GA	1.0488	0.3181	0.2139	9	10	19.6
HBGAPSO	1.0476	0.3193	0.2134	10	9	16.2
BACO	1.0467	0.3172	0.2129	9	9	14.8

5.3. IEEE 69-bus distribution system

To test the potential of the proposed method in solving bigger systems, a standard IEEE 69-bus distribution system is considered. The studied IEEE 69-bus test distribution system is shown in Figure 10. The detailed specifications of this network is presented in [27], where the detailed data of the capacitors used in the network are shown in Table 6. The impedance of the transformer between nodes 0 and 1 is (0.012 + j0.12) per unit. The rated capacity for DGs installed on bus 19 and 61 is 0.4 and 1.3 MW, respectively. The other conditions of this system are considered like the 33-bus distribution system. The daily profile of the system is according to Figure 5. In the case of M = 8, the resulting load profiles are shown in Figure 5. Similar to the 33-bus system, the Volt/VAr control will be tested in 4 different cases. The difference is that Q_{DG19} = 0.1 MVAr and Q_{DG61} = 0.3 MVAr in Case 3, and $Q_{DG19,\min}$ = –0.1, $Q_{DG61,\max}$ = 0.1, $Q_{DG19,\min}$ = –0.3 and $Q_{DG61,\max}$ = 0.3 MVAr in Case 4.

Table 6. Capacitor data for the IEEE 69-bus distribution system.

Capacitor number	C_1	C_2	C_3	C_4	C_5	C_6
Capacity (kVAr)	300	250	250	300	250	300
Location	1	43	47	58	64	66

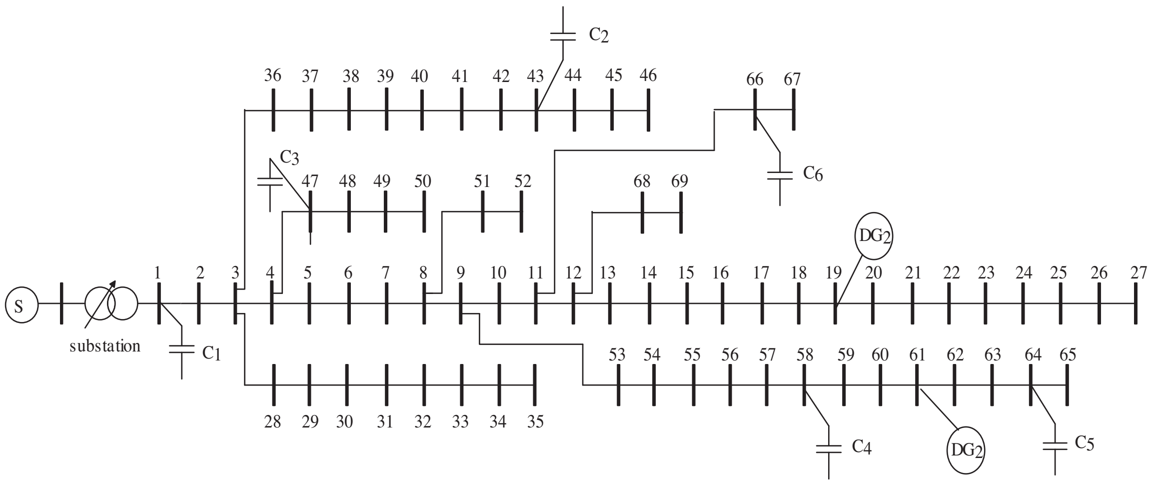

Figure 10. One-line diagram of the 69-bus IEEE distribution system.

Among the 4 cases, the best simulation results were obtained by BACO, which are presented in Table 7. It can be seen from Table 7 that the presence of DG will give minimum results when compared with the results obtained in the case without DG. The most significant reduction of energy losses will be obtained when the DG generates constant reactive power. The system voltage profile at bus 65, for the initial state and after optimization in the 4 cases, is shown in Figure 11. It can be concluded that the voltage profiles are greatly improved after optimization and the system performance can be improved under the proper control.

Figure 12 shows the voltage deviation for 4 cases using BACO. It can be seen that the average voltage deviations are reduced evidently when DG exists in the system.

Table 7. The best results for different cases using BACO in the 69-bus distribution system.

	Case 1	Case 2	Case 3	Case 4
f_1 (MWh)	2.2213	0.5641	0.3675	0.3843
f_2 (pu)	0.4564	0.1078	0.0884	0.1519
f_3 (pu)	0.3625	0.1396	0.1238	0.1201
f_4	9	4	2	9
f_5	8	7	9	5

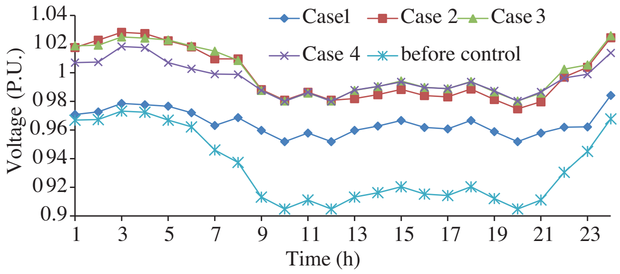

Figure 11. Voltage profile for bus 65 in the 69-bus distribution system for different cases.

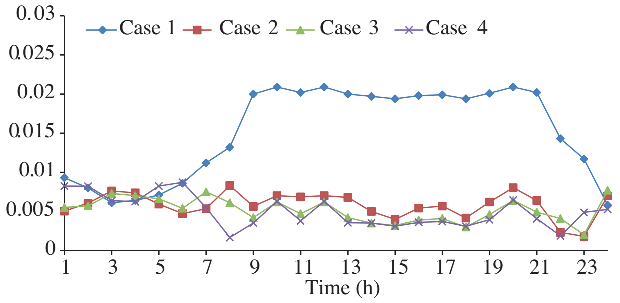

Figure 12. Voltage deviation for 4 cases in the 69-bus distribution system.

The average results of 100 trials for the total voltage deviation on the secondary bus, the total energy losses, the number of OLTC and capacitor operations, and the voltage fluctuations in the distribution systems obtained using the 3 procedures are presented in Table 8 and the results confirm the effectiveness of the proposed method.

Table 8. Average results of 100 trials from the different optimization procedures: GA, HBGAPSO, and BACO.

Method	f_1 (MWh)	f_2(pu)	f_3(pu)	f_4	f_5
GA	0.3703	0.0897	0.1257	4	10
HBGAPSO	0.3692	0.0894	0.1252	3	10
BACO	0.3681	0.0889	0.1241	3	9

6. Conclusion

A new multiobjective daily Volt/VAr control approach for distribution systems including DG is proposed in this paper. The main purpose was to determine optimum dispatch schedules for the OLTC settings, substation-switched capacitors, and feeder-switched capacitors based on the day-ahead load forecast. The voltage deviation on the secondary bus of the main transformer, the total energy losses, the number of OLTC and capacitor operations, and the voltage fluctuations in the distribution systems have been considered as objectives. The multiobjective problem has then been solved using the AHP method and BACO algorithm. The proposed approach has been tested and examined on 33-bus and 69-bus distribution power systems. The simulation results revealed that the proposed method is very effective in reaching a proper dispatching schedule and bus voltage magnitude with the desired limits. The results using the proposed method were compared to those reported in the literature. The results confirm the potential of the proposed approach and show its effectiveness and superiority over the GA and HBGAPSO algorithms.

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