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BACO–Based Fuzzy Multiobjective Approach to Volt/VAr Control in Distribution Networks

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Abstract:

Voltage and reactive (Volt/VAr) control is one of the imperative control schemes in distribution networks, which can be influenced by distributed generations (DG), this paper presents a new multiobjective Volt/VAr control approach in distribution networks with distributed generation (DG). A binary ant colony optimization (BACO) based fuzzy multiobjective approach is used to solve Volt/VAr control, where Dispatch schedules for on-load tap changer (OLTC) settings at substations, substation switched capacitors and feeder-switched capacitors are selected as control variables. A time-interval based control strategy is used to simplify the control actions for OLTC at substations. The proposed Volt/VAr control approach is tested on IEEE 33-bus system and its performance is compared with genetic algorithm and particle swarm optimization algorithm. Simulation results show the BACO algorithm has better outperforms than other algorithms.

Keywords **—Distributed generations, BACO algorithm, Fuzzy system, Multi-objective, Volt/VAr control.**

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I. INTRODUCTION

Nowadays, research in the Volt/VAr control for distribution systems can be divided into two 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 setting 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].

Recently, multi-objective optimization approaches for reactive power control have become more attractive [6–14]. But, the attention has been focused on power losses and voltage deviation. Up to now, various mathematical optimization algorithms, such as gradient-based algorithms, linear programming, non-linear programming and interior point methods, have been widely used to solve this problem [15-17]. However, the Volt/VAr control is an optimization problem of non-continuous and non-linear function. These conventional techniques need many mathematical assumptions, such as differential properties of the objective functions and unique minimum existing in problem domains, and often trap in local optimal solutions. In recent years, evolutionary algorithms [6-12], such as genetic algorithm, particle swarm optimization and evolutionary strategy, have been applied to Volt/VAr control problem. Theoretically, these techniques converge to the global optimum solution with probability one. They are useful especially when other optimization methods fail in finding the optimal solution.

R.h Liang et al. presented a fuzzy optimization approach for solving the Volt/VAr control problems in a distribution system with uncertainties. Wind turbines are being considered in the study distribution system in [11]. In this paper, the Volt/VAr control is formulated as a multi-objective optimization problem. The objectives consist of the voltage deviation on the secondary bus of the main transformer, Total electrical energy losses, Reactive power flow through the OLTC and voltage fluctuation in distribution systems. In this paper a method based on fuzzy optimization strategy and Binary ACO (BACO) algorithm is employed that uses a special encoding method to avoid such problems. The DG considered in this paper is of a synchronous machine-based DG, which is normally used for combined heat and power (CHP) applications, one of the most significant DG applications in MV distribution systems [1].

II. PROBLEM FORMULATION

With the development of a distribution management system, the loads along each feeder bus and secondary substation bus for the next day can be obtained using short-term load forecasting techniques [4]. Generally, in a distribution system, a main transformer is installed with a load tap changer (LTC) which can adjust its voltage ratio with respect to the present or expected load, to compensate the voltage drop over the transformer and upstream lines [5]. Voltage at the primary bus of a substation changes slightly over a day and is therefore assumed to have a constant value in this paper. Shunt capacitors that are installed on the secondary bus (substation capacitors) are intended to compensate the reactive power flow through the substation transformer. In addition, the feeder capacitors that are installed on each feeder will maintain the voltage on the feeder, as a supplement to the voltage regulation by the OLTC and will compensate reactive power on the feeder.

The objective of the Volt/VAr control considering DG is to determine a proper dispatching schedule of OLTC tap position and shunt capacitors status for the day ahead. Meanwhile, the voltage deviation on the secondary bus of the main transformer, Total electrical energy losses, the Reactive power flow through the OLTC and voltage fluctuations in 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 follows:

A. *Objective functions*

In this paper, The objective function of Volt/VAr control consist of the voltage deviation on the secondary bus of the main transformer, real power loss on feeders, the Reactive power flow through the OLTC and voltage fluctuations in distribution systems:

Total electrical energy losses: The first objective is to minimize total active power losses for the day ahead. The losses considered here are the losses in the distribution system plus the transformer losses. The load profile is developed with a 1h interval between two subsequent stages:

minimize $f_1 = \sum_{i=1}^{N} P_{Loss,i}$ (1)

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

Voltage deviation on the secondary bus: During the dispatching period, the voltage deviation on the secondary bus of main transformer should be improved and can be expressed as.

minimize $f_2 = \sum_{i=1}^{N} |\Delta V_{2,i}|$ (2)

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

Voltage violation: Treating bus voltage limits as constraints often make all the voltages move toward their maximum limits after optimization. One of the effective ways to avoid this situation is to choose the voltage violation as an objective function, that is:

minimize $f_3 = \frac{1}{N_L} \sum_{h=1}^{N_L} \sum_{i=1}^{N} |V_{h,i} - V_{h,i-1}|$ (3)

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

Reactive power flow through the OLTC: To arrest the reactive power flow through the OLTC can improve the voltage profile and reduce power loss. The mathematical expression can be written as

minimize $f_4 = \sum_{i=1}^{N} |Q_{OLTC,i}|$ (4)

Where $Q_{OLTC,t}$ is the reactive power flow through the OLTC at time i.

B. Constraints

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

Bus voltage magnitude:

$V_{min} < V_{h,i} < V_{max}$(5)

Line flow limit:

$S_{TX,i} \leq S_{TX,rat}$ (6)

Daily number of OLTC operations limits:

$\sum_{i=1}^{N} |TAP_i - TAP_{i-1}| \leq TAP_{max}$ (7)

Daily number of switching operations for shunt capacitors limits:

$\sum_{i=1}^{N} (C_{k,i} \otimes C_{K,i-1}) \leq CM_k$ (8)

Where $S_{TX,i}$ is apparent power flow on substation transformer at time, $S_{TX,rat}$ is the substation transformer rating, The symbol ⊗ will represent the logical Exclusive-OR operator, V_{min} is the minimum allowed voltage, V_{max} is the maximum allowed voltage, TAP_{max} is the maximum switching operation for OLTC and CM_k is the maximum switching operation for capacitor k.

III. FUZZY OPTIMIZATION STRATEGY

In this section, a fuzzy optimization approach for the multi-objective daily Volt/VAr control problem is proposed. The method proposed here, optimizes the performance with respect to four important Objective functions described above, at the same time minimum degree of satisfaction among the Objective functions must be maintained. Therefore, the problem stated in the section (2) is transformed into a single-objective model based on fuzzy membership functions. A fuzzy set is a set without crisp boundary [18] i.e., transition from "belong to a set" to "not belong to a set" is gradual. This smooth transition from "belong to" to "not belong to" is characterized by a membership function (MF). MF gives desired flexibility to a fuzzy set. There are several classes of parameterized membership functions, such as Triangular membership function, Trapezoidal membership function, Gaussian membership function, Generalized bell membership function, etc. [19]. The choice of membership function and its parameters depends on the desired input/output mapping. In this work, Trapezoidal membership function is used for fuzzification of the objectives.

In the fuzzy optimization, the i-th objective function is modeled by a linear membership function (shown in Fig. (1)) as follows:

$\mu_{Fi}(X) = \frac{f_i(X) - f_{imax}}{f_{imax} - f_{imin}}$(9)

Where f_{imax} and f_{imin} are the maximum and minimum possible values in the feasible interval for the function $f_i(X)$, respectively. In the proposed algorithm, f_{imax} is the initial value of objective function and f_{imin} is the optimal value when an optimization problem with $f_i(X)$ as the single-objective function is solved. The high objective is given a low value, whereas low objective is assigned a high value. For fuzzy multiple objectives, the fuzzy solution can be calculated as:

$\mu_D(X) = \min\left(\mu_{f1}(X), \mu_{f2}(X), \mu_{f3}(X), \mu_{f4}(X)\right)$ (10)

The maximum value of $\mu_D(X)$ is considered as the optimal solution.

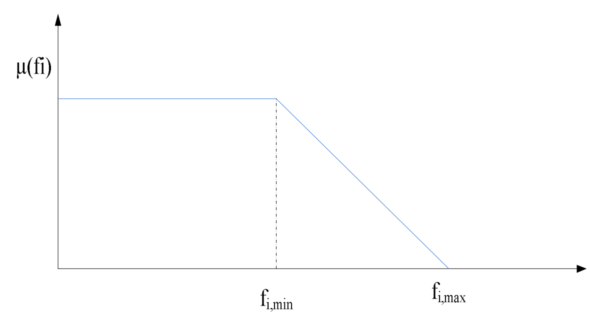

Fig. 1 Membership function of the i-th objective function

IV. ANT COLONY OPTIMIZATION

A. Binary Ant Colony Optimization

A continuous optimization problem can be described as

$$\min \quad J = f(x) \qquad (11)$$
$$x_{min} \leq x \leq x_{max} \quad ; \quad x = (x_1, x_2, \ldots, x_n) \in R^n$$

The feasible regions of all variables in x should be represented by binary strings in order to construct search space before binary ACO (BACO) begin. Every variable x_i in candidate solution $\{x_1,x_2, \ldots,x_n)$ is expressed by an N-bits 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 Fig.2. The nodes of the graph consist of zero and one which are the state candidates of every bit. The graph arcs connect possible state transition routes between two adjoining bits.

In each iteration, every ant travels all N nodes of n variables to construct a solution candidate. Its trace generates n binary strings, and the kth binary string can be decoded and mapped into X_k by converting it to a decimal number. Then 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 the state a to b at the jth bit of the variable x_k, with a, b $\in\{0, 1\}$. As shown in Fig. 2, there are two arcs leading to next vertex for every bit. An ant selects its route according to the pheromone distribution on both arcs. It moves towards next node according to the probability distribution given by (12),

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

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

$$\tau_{ab}^{ki}(t+1) = \rho.\tau_{ab}^{ki}(t) + \Delta\tau_{ab}^{k}(t) \quad (13)$$

Where, ρ represents the durability of the track (0≤ρ≤1), $\Delta\tau_{ab}^{k}(t)$ is the incremental pheromone, which can be computed by [22]:

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

Where s^{ib} is 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 the ants follow the same tour, because of the excessive growth of pheromone trails on arcs of a good, although suboptimal, tour. To counteract this effect, a modification applied in this paper is introduced by MMAS[1] that it limits the possible range of pheromone trail values to the interval $[\tau_{min}, \tau_{max}]$ [24]. In MMAS, lower and upper limits τ_{min} and τ_{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]:

$$\tau_{max} = \frac{1}{(1-\rho) * f(s^{opt})}$$

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

Where $f(s^{opt})$ is the global-best solution.

The steps of BACO algorithm are as follows:

Step 1: Initialize parameters.

For the BACO proposed in this paper, the parameters choosing is researched meanwhile, so as to get the best effect. It is very important to select the parameter of BACO, and different parameters will have the different result. 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 is defined as in equation (12).

Step 4: Fitness evaluation

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

Step 5: Apply updating rule

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

Step 6: Pheromone trail limits

Lower and upper limits τ_{min} and τ_{max} on the possible pheromone values on any arc are imposed in order to avoid search stagnation where is described in equation (15).

Step 7: End conditions

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

The flowchart of the proposed ant colony algorithm is shown in Fig. 2**.**

B. Encoding

Shunt capacitors: Feeder capacitors and substation capacitors are allowed at most to switch 3 and 4 in a day, respectively. If for any capacitor, 24-bit is consider, which each bit represents capacitors on/off status in the hour, then the total number of bits of the problem are very much and therefore the time to achieve optimal solution increases. So, in this paper, for capacitors just the time of capacitor switches is considered. Since each day is 24 hours for each switch operation five bits is considered. So, the number of bits intended for encoding the feeder capacitors and substation capacitors are equal to 15 and 20, respectively, which this value is not greater than 24. If, this number is multiplied by the total number of capacitors the genome length will be significant and therefore the search space to achieve optimal solution will decrease.

OLTC: It is difficult to specify the controlling parameters when applying automated techniques to control OLTC 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 OLTC settings based only on load forecasting [1, 2]. However, to achieve the 24-h optimization of multi-objective 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 control actions are performed only once. So, in this study the method described in [4] is applied.

To meet this goal, Firstly, 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]:

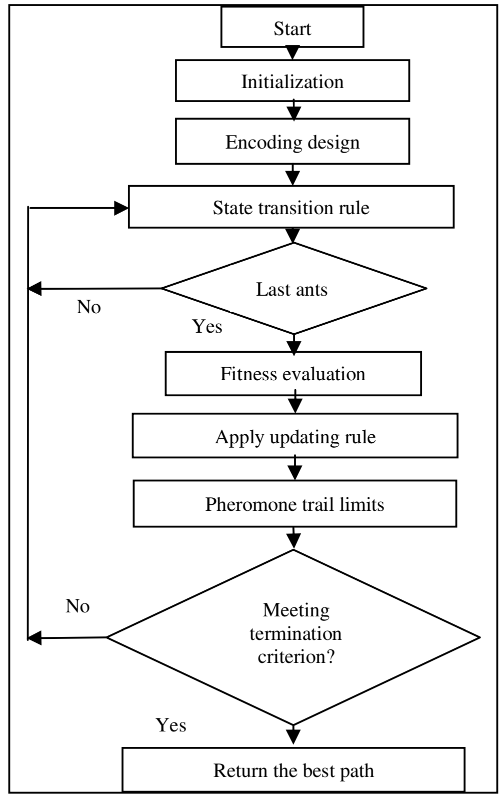

Fig.2Flowchart of the BACO

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

Where:

P_{ij}: active power of the jth load point of the ith load level

Q_{ij}: reactive power of the jth load point of the ith load level

AVP_i: average active power of the ith load level

AVQ_i: average reactive power of the ith load level

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

V. THE PROPOSED ALGORITHM FOR VOLT/VAR CONTROL

The multi-objective Volt/Var control problem can be converted into a single-objective optimization by the fuzzy optimization method. A single-objective optimization problem will easily be handled by the

BACO approach a schematic flowchart of the computational procedure is shown in Fig. 3 and is described as follows:

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

Step 2: Determine the start and end times of each load level based on section 4-3

Step 3: In order to determine fuzzy objective function for each individual, at first, the distribution load flow is run based on the state variables. Based on the results of distribution load flow, the objective function values ($f_1(x)$, $f_2(x)$, $f_3(x)$ and $f_4(x)$) are calculated and the constraints are checked. Then, the membership function values are calculated by using the values of objective functions. The minimum value of these is considered the objective function.

Step 4: Apply BACO

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

VI. SIMULATION RESULTS

In this part, the multi-objective Volt/VAr control in distribution networks considering DG is tested on an IEEE 33-bus distribution system. A single diagram of this network is shown in Fig. 4. The detailed specification of this network is presented 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. Tables. 1 and 2 show specifications of capacitors and DGS 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 voltage for each bus is 1.05 per unit and 0.95 per unit, respectively. Voltage at the primary bus of a substation is 1.0 per unit. Loads are constant power loads with a daily profile according to Fig. 5.

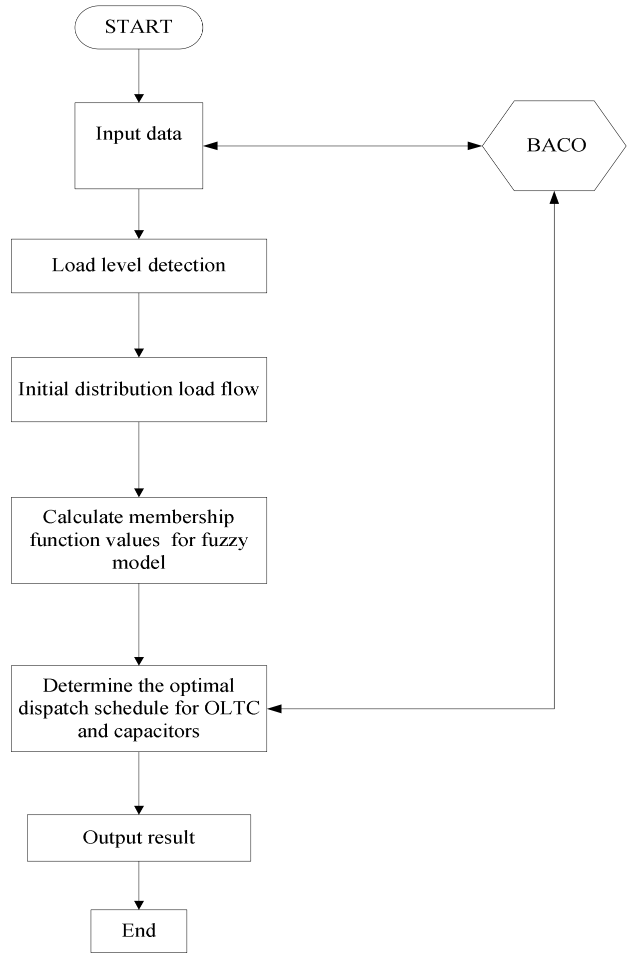

Fig.3 Flowchart of the Volt/VAr control algorithm

For the case of M=8, the resulted load profile are shown in Fig. 6, where the dash dot lines indicate the boundaries between load levels.

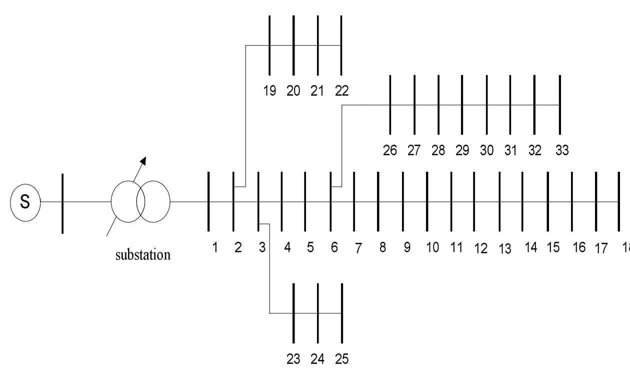

Fig. 4a single line diagram of IEEE 33-bus distribution system

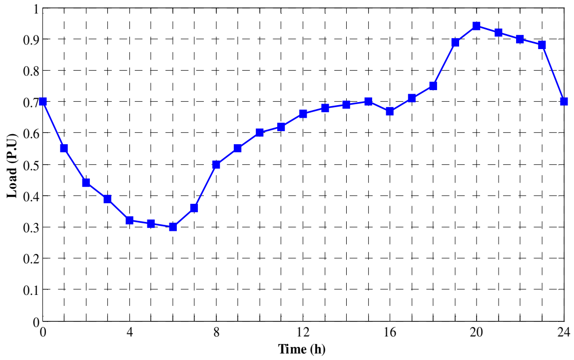

Fig. 5 Daily load profile

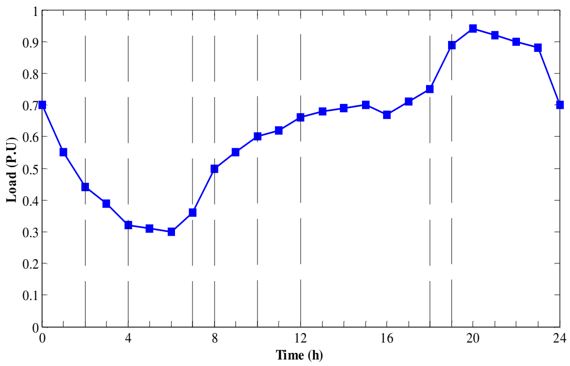

Fig. 6 Eight-load level partition results

TABLE I
CHARACTERISTIC OF CAPACITORS OF 33-BUS DISTRIBUTION SYSTEM

Capacitor	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Capacity (KVAr)	150	150	150	150	150	150	150	150
Location	1	12	16	28	29	30	31	32

TABLE III
CHARACTERISTIC OF DISTRIBUTED GENERATIONS OF 33-BUS DISTRIBUTION SYSTEM

DG	Capacity (kw)	Location	Power factor Case 3	Power factor Case 4
G_1	400	10	0.97 lag	0.97 lag to 0.97 lead
G_2	400	16	0.97 lag	0.97 lag to 0.97 lead
G_3	400	32	0.97 lag	0.97 lag to 0.97 lead

The DG considered in this paper is of a synchronous machine-based DG. The Volt/VAr control presented in this paper will be tested on four different cases, i.e., without DG in the system (which will be called as case 1), with DG operating at a unity power factor (case 2), at a constant reactive power output (case 3), and at a constant voltage with reactive power limits (case 4).

DG impacts on Volt/VAr control can be investigated from the Total energy losses, reactive power flow through the OLTC, voltage deviation on the secondary bus of the main transformer and voltage fluctuations shown in Table. 3. The simulation results show that the DGs improve performance of the system. If the DG generates constant reactive power, the reactive power flow through the OLTC is minimized. The energy losses shown in Table.3 indicate that the DG operating at unity pf will give lower losses than DG which generates constant reactive power. The daily voltage fluctuation shown in table.3 indicates that the presence of the DG decreases the bus voltage fluctuation, where the most significant reduction will be obtained in case 4.

Table. 4 shows daily optimal dispatch schedule of capacitors and OLTC in case 3 based on the load levels shown in Fig. 6 The number of switching operations for OLTC in the whole day is 4. C_1 switch one time in a day. Feeder capacitors switch 11 times for the whole day. The voltage at bus-18 is the lowest in the test system. Voltage profile at bus-18, before control and after using proposed algorithm in all cases are shown in Fig. 7 the figure indicates that in all cases, the voltages always stay within the allowed range given by (5), and the voltage profile at bus-18 is greatly improved in the presence of the DG units. Fig. 8 shows voltage deviation for all cases using BACO. A daily real power loss comparison between four cases is shown in Fig. 9

TABLE IIIII
THE BEST RESULTS FOR DIFFERENT CASES USING BACO IN 33-BUS DISTRIBUTION SYSTEM

	Case 1	Case 2	Case 3	Case 4
f_1 (MWh)	1.3764	0.4302	0.4318	0.4381
f_2(pu)	0.5631	0.1490	0.0815	0.1140
f_3 (pu)	0.2785	0.1544	0.1556	0.1426
f_4 (MVAr)	9.9837	9.1008	7.2393	9.1570

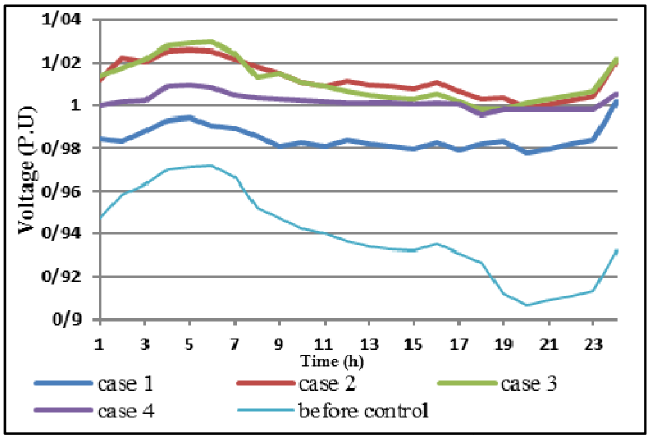

Fig. 7 Voltage profile for bus-18 for different cases in 33-bus IEEE distribution system

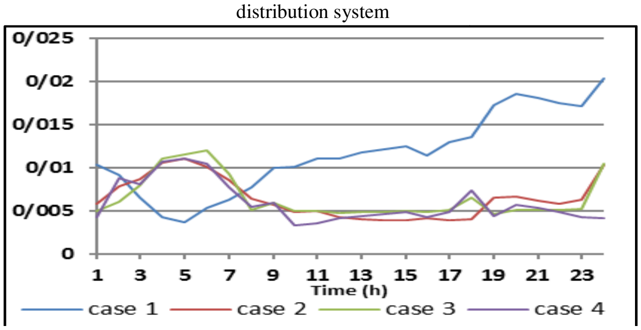

Fig. 8 Voltage deviation for four cases in 33-bus IEEE distribution system

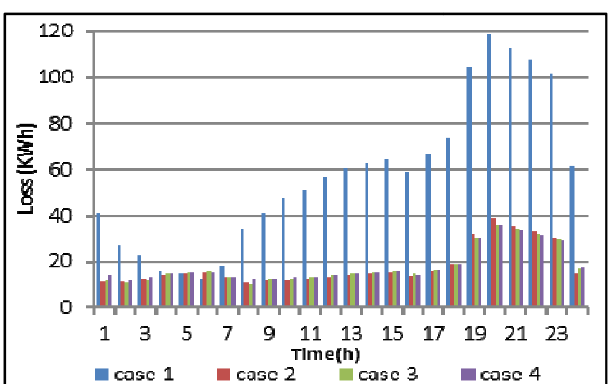

Fig. 9 Comparison of daily real power losses in 33-bus distribution system in four cases

TABLE IVV
DAILY OPTIMAL DISPATCH SCHEDULE OF CAPACITORS AND OLTC IN CASE 3

Hour	TAP	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
1	+1	1	0	0	0	1	0	1	**0**
2	0	1	0	0	0	1	0	1	**0**
3	0	1	0	0	0	1	0	1	**0**
4	0	1	0	0	0	1	0	0	**1**
5	0	1	0	0	0	1	0	0	**1**
6	0	1	0	0	0	1	0	0	**1**
7	0	1	0	0	0	1	0	0	**1**
8	0	1	0	0	0	1	1	0	**1**
9	0	1	1	0	0	1	1	1	**1**
10	0	1	1	0	0	1	1	1	**1**
11	0	1	1	0	0	1	1	1	**1**
12	0	1	1	0	1	1	1	1	**1**
13	0	1	1	0	1	1	1	1	**1**
14	0	1	1	0	1	1	1	1	**1**
15	0	1	1	0	1	1	1	1	**1**
16	0	1	1	0	1	1	1	1	**1**
17	0	1	1	0	1	1	1	1	**1**
18	0	1	1	0	1	1	1	1	**1**
19	+2	1	1	0	1	1	1	1	**1**
20	+2	1	1	1	1	1	1	1	**1**
21	+2	1	1	1	1	1	1	1	**1**
22	+2	1	1	1	1	1	1	1	**1**
23	+2	1	1	1	1	1	1	1	**1**
24	+2	1	1	1	1	0	1	1	**1**

With the same control variable limits, initial conditions and other system data, the best, average, and worst results of 100 trials and their average computation time for total voltage deviation on the secondary bus, Total energy losses, the reactive power flow through the OLTC and voltage fluctuations in distribution systems obtained by using the three procedures: genetic algorithm, PSO and BACO in case 3 are given in Table. 5. It is obvious that the average values of four objective functions considered in this paper, from the BACO are lower than those from the PSO and GA. For example, the Total energy losses with using GA, PSO and BACO algorithms are 436.5, 434.3 and 432.6 KWh, respectively. It is clear that Total energy losses are greatly reduced by using the BACO algorithm.

In addition, this result shows that the proposed method has the ability to find a good solution. The difference of Total energy losses, total reactive power flow through the OLTC, total voltage deviation on the secondary bus and voltage fluctuations in the system between the best and worst results is only 1.9 KW, 19 KVAr, 0.0003 and 0.0005 P.U, respectively. In other words, the differences are just only 0.44%, 0.27%, 0.37% and 0.32%, respectively. It is obvious that the proposed algorithm outperforms the other methods.

Fig. 10 shows the convergence characteristics of GA, PSO and BACO for the best solution in case 3. For the sake of conciseness, Fig. 10 shows only the convergence characteristics of Total energy losses objective function. It can be seen that the value of the Total energy losses using GA, PSO and BACO algorithms are converged to the global minimum point after about 90, 80 and 65 iterations, respectively.

According to Table. 5, the average computing time for the GA, PSO and BACO algorithms is 19.6, 16.2 and 14.8 min, respectively. It can be seen that the BACO algorithms have a minimum execution time between three methods.

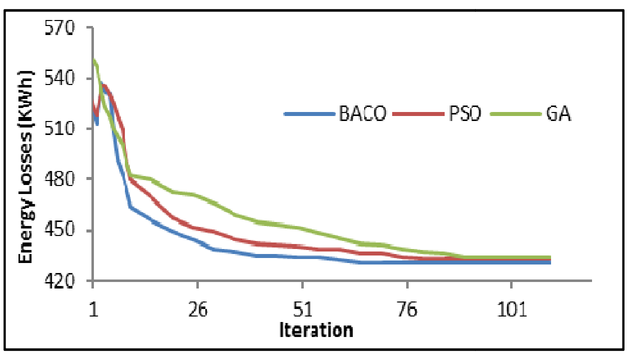

Fig. 10 Convergence characteristics of the GA, PSO and BACO for the best solutions in case 3

TABLE V
STATISTICAL RESULTS OF 100 SIMULATION TESTS FORM DIFFERENT OPTIMIZATION PROCEDURES: GA, PSO AND BACO FOR 33-BUS DISTRIBUTION SYSTEM

Method		BACO	PSO	GA
Best	f_1 (KWh)	431.8	433.2	434.3
	f_2 (pu)	0.0815	0.0819	0.0818
	f_3 (pu)	0.1556	0.1559	0.1560
	f_4 (Kvar)	7239.5	7255.2	7264.6
Average	f_1 (MWh)	432.6	435.1	436.5
	f_2 (pu)	0.0816	0.0821	0.0821
	f_3 (pu)	0.1558	0.1562	0.1563
	f_4 (Mvar)	7252.2	7270.3	7284.3
Worst	f_1 (MWh)	433.7	438.6	438.1
	f_2 (pu)	0.0818	0.0822	0.0824
	f_3 (pu)	0.1561	0.1565	0.1568
	f_4 (Mvar)	7258.7	7301.6	7312.4
Calculation time (min)		14.8	15.1	19.6

VII. CONCLUSIONS

In this paper, a new multi-objective daily Volt/VAr control method for distribution systems including DG is proposed. a binary ant colony optimization (BACO) based fuzzy multiobjective approach has been used to solve Volt/VAr control, where Dispatch schedules for on-load tap changer (OLTC) settings at substations, substation switched capacitors and feeder-switched capacitors have been considered as control variables. To illustrate the efficiency of the proposed method, a 33-bus distribution power system was performed. Simulation results indicated that the proposed method was very effective in reaching a proper dispatching schedule and the bus voltage magnitude with the optimal constraints. The simulation results of BACO algorithm in compare of GA and PSO algorithms indicate that the BACO leads to very accurate results and converges very rapidly.

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