Optimal Reactive Power Dispatch Using Ant Colony Optimization Algorithm

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Abstract–**This paper proposes a procedure for solving the optimal reactive power dispatch (ORPD) problem using ant colony optimization (ACO) algorithm. The objective of the ORPD is to minimize the transmission line losses under control and dependent variable constraints using proposed sensitivity parameters of reactive power that dependent on a modification of Fast Decoupled Power Flow (FDPF) model. The ACO algorithm is applied to the IEEE standard 14-bus and a real power system at west delta network as a part of the Unified Egyptian Network (UEN). Simulation results show the capability of the proposed ACO algorithm for the ORPD problem compared with those obtained using the conventional optimization techniques as linear programming (LP), genetic algorithm (GA) and particle swarm optimization (PSO) technique.**

Index Terms— **Ant colony optimization, reactive power dispatch.**

I. INTRODUCTION

ORPD is one of the optimization problems in power systems that optimized the control variables by conventional, intelligence and modern optimization techniques. The objective function of ORPD is to minimize the transmission line losses by optimizing the control variables such as generation voltages, switchable reactive power and on-load tap changers (OLTC) under control and dependent variable constraints.

Subbaraj and Rajnarayanan [1] proposed self-adapted real coded genetic algorithm (SARGA) to solve optimal reactive power dispatch (ORPD) problem. The self-adaptation in real coded genetic algorithm (RGA) introduced by applying the simulated binary crossover (SBX) operator, binary tournament selection and polynomial mutation. The problem formulation involves continuous (generator voltages), discrete (transformer tap ratios) and binary (VAR sources) decision variables.

Aruna and Devaraj [2] presented real coded genetic algorithm (RGA) for solving the multi-objective ORPD problem in a power system. Modal analysis of the system used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting taken as the optimization variables.

Mahadevan and Kannan [3] solved the ORPD problem by minimizing the active power losses for a fixed economic power dispatch by adjusting the control variables using particle swarm optimization (PSO) technique. To overcome the drawback of premature convergence in PSO, a learning strategy introduced in PSO, and this approach called, comprehensive learning particle swarm optimization (CLPSO) also applied to the proposed problem.

Subbaraj and Rajnarayanan [4] proposed a two-phase hybrid PSO approach to solve ORPD problem. In this hybrid approach, the phase-1 used PSO to explore the optimal region and the phase-2 applied direct search as local optimization technique for finer convergence.

Through few recent years, ACO algorithms are employed to solve optimization problems in different fields with more accurate and efficiently solution compared with conventional and other modern optimization algorithms. Nakawiro and Erlich [5] presented a hybrid method for solving voltage stability constrained optimal reactive power dispatch (VSCORPD) problem, with minimizing the energy loss at the current time interval and the cost of adjusting discrete control devices while maintaining system security and voltage stability constraints within the permissible limits. An artificial neural network (ANN) is trained to approximate the voltage stability margin during the optimization process, while modified ACO used to solve the VSCORPD.

Abbasy and Hosseini [6] proposed a novel ACO-based ORPD approach and four different ACO algorithms, including the simple ant system and three of its direct successors, elitist ant system (AS), rank-based AS and max-min AS used to solve the ORPD problem, with minimizing the real power loss under decision and dependent variables constraints.

In this paper, an approach is proposed to solve the ORPD problem using the ACO algorithm, which based on the behavior of real ants for searching the shortest route between the colony and the source of food based on the indirect communication media, called pheromone. The minimization of the transmission line losses are considered as an objective function with control and dependent variable constraints.

II. PROBLEM FORMULATION

The ORPD problem can be expressed as an optimization problem with the transmission line losses that are a function in the generator voltages and switchable reactive power, which are defined as:

$$Min\Delta P_L = \sum_{G=1}^{NG}\left(\partial P_L / \partial V_G\right)\Delta V_G + \sum_{SW=1}^{NSW}\left(\partial P_L / \partial Q_{SW}\right)\Delta Q_{SW} \qquad (1)$$

Where,

ΔP_L is the objective function of the change in transmission line losses.

ΔV_G and ΔQ_{SW} are the changes in the control variables of generation voltages and switchable reactive power, respectively.

NG is the number of generation buses.

NSW is the number of buses which the switchable reactive sources are located.

Now, the changes in transmission line losses with respect to changes in generator voltage can be derived based on the load flow equations as;

$$S_i = V_i I_i^* \qquad (2)$$
$$= |V_i|\sum_{j=1}^{N}\left\{\left[G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right] + j\left[G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right]\right\}|V_j|$$

also;

$$S_i = P_i + jQ_i \qquad (3)$$

From equations (2) and (3), the active power at bus i can be formulated as:

$$P_i = |V_i|\sum_{j=1}^{N}\left[G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right]|V_j| \qquad (4)$$

At, $i = j$, equation (4) can be rewritten as;

$$P_i = V_i^2 G_{ii} + |V_i|\sum_{j=1,j\neq i}^{N}\left[G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right]|V_j| \qquad (5)$$

Now, the values of $\partial P_i/\partial V_i$ and $\partial P_j/\partial V_i$ can be calculated by differentiating equation (5) as:

$$\left.\partial P_i / \partial V_i\right|_{i\in NG} = 2V_i G_{ii} + \sum_{j=1,j\neq i}^{N}\left[G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right]|V_j| \qquad (6)$$

$$\left.\partial P_j / \partial V_i\right|_{j\notin NG} = |V_j|\left[G_{ji}\cos\delta_{ij} - B_{ji}\sin\delta_{ij}\right] \qquad (7)$$

Where, $Y_{ij} = -1 / Z_{ij} = G_{ij} + j B_{ij}$; is the line admittance between buses i and j. δ_i and δ_j are the angles of the voltages at buses i and j, respectively.

Also, the change in transmission line losses due to changes in switchable reactive power can be written as:

$$\partial P_L / \partial Q_{SW} = \left(\partial P_L / \partial V_{SW}\right)\left(\partial V_{SW} / \partial Q_{SW}\right) \qquad (8)$$

Where, $\partial V_{SW} / \partial Q_{SW}$: is the change of switchable voltage buses with respect to change in switchable reactive power at that bus. The objective function (1) is subjected to the following constraints:

a) Control variable constraints

• Generation voltage constraints

The change in generator voltage must be within their permissible limits as:

$$\Delta V_G^{\min} \leq \Delta V_G \leq \Delta V_G^{\max} \qquad (9)$$

Where,

$$\Delta V_G^{\min} = V_G^{\min} - V_G^{init}$$
$$\Delta V_G^{\max} = V_G^{\max} - V_G^{init}$$

Where,

V_G^{init} is the initial value of the generator voltage at each generator bus.

V_G^{min} and V_G^{max} are the minimum and maximum of generation voltages, respectively.

ΔV_G^{main} and ΔV_G^{max} are the minimum and maximum changes in generation voltages, respectively.

• Switchable reactive power constraints

The change in switchable reactive power must be within their permissible limits as:

$$\Delta Q_{SW}^{\min} \leq \Delta Q_{SW} \leq \Delta Q_{SW}^{\max} \qquad (10)$$

Where,

$$\Delta Q_{SW}^{\min} = Q_{SW}^{\min} - Q_{SW}^{init}$$
$$\Delta Q_{SW}^{\max} = Q_{SW}^{\max} - Q_{SW}^{init}$$

Where,

Q_{SW}^{init} is the initial value of the switchable reactive power.

Q_{SW}^{min} and Q_{SW}^{max} are the minimum and maximum of switchable reactive power, respectively.

ΔQ_{SW}^{main} and ΔQ_{SW}^{max} are the minimum and maximum changes in switchable reactive power, respectively.

b) Dependent variable constraints

• Load voltage constraints

The voltage at each load bus must be within their permissible limits as:

$$\Delta V_L^{\min} \leq \Delta V_L \leq \Delta V_L^{\max} \qquad (11)$$

Where,

$$\Delta V_L^{\min} = V_L^{\min} - V_L^{init}$$
$$\Delta V_L^{\max} = V_L^{\max} - V_L^{init}$$

Where,

V_L^{init} is the initial value of the voltage at each load bus.

V_L^{min} and V_L^{max} are the minimum and maximum of load bus voltages, respectively.

ΔV_L^{main} and ΔV_L^{max} are the minimum and maximum changes in load bus voltages, respectively.

• Generation reactive power constraints

The reactive power of each generator must be within their permissible limits as:

$$\Delta Q_G^{\min} \leq \Delta Q_G \leq \Delta Q_G^{\max} \qquad (12)$$

Where,

$$\Delta Q_G^{\min} = Q_G^{\min} - Q_G^{init}$$
$$\Delta Q_G^{\max} = Q_G^{\max} - Q_G^{init}$$

Where,

Q_G^{init} is the initial value of reactive power at generation buses.

$Q_G{}^{min}$ and $Q_G{}^{max}$ are the minimum and maximum values of reactive power at generation buses, respectively.
$\Delta Q_G{}^{main}$ and $\Delta Q_G{}^{max}$ are the minimum and maximum changes in reactive power at generation buses, respectively.

III. PROPOSED SENSITIVITY PARAMETERS

The FDPF method is one of the load flow methods that assumed the changes in active power flows due to changes in voltage phase angles are higher than the changes due to voltage magnitudes. On the other hand, the changes in reactive power flows due to changes in voltage magnitudes are higher than the changes due to voltage phase angles. So, it can be written as:

$$[\Delta P/V] = [B'] [\Delta\delta] \quad \text{and} \quad [\Delta Q/V] = [B''] [\Delta V]$$

Where,

$[\Delta P]$ and $[\Delta Q]$ are the vectors of active and reactive power mismatches, respectively.
$[B']$ and $[B'']$ are the susceptance matrices.
$[\Delta\delta]$ and $[\Delta V]$ are the vectors of changes in voltage angles and magnitudes, respectively.

In this paper, the ORPD problem is based on the second equation of the FDPF as:

$$[\Delta Q/V] = [B''] [\Delta V] \tag{13}$$

Where, B'' is the susceptance matrix as:

$$B_{ii}^{"} = \sum_{j=1, j\neq i}^{N-1} 1/X_{ij} ; i = 1,2,.....,\ N-1$$

$$B_{ij}^{"} = B_{ji}^{"} = -1/X_{ij} ; i,j = 1,2,.....,\ N-1$$

Where, X_{ij}: is the line reactance between buses i and j.

Now, equation (13) can be rewritten in terms of control and dependent variables as:

$$\begin{bmatrix} \Delta Q_G /V_G \\ \Delta Q_L /V_L \end{bmatrix} = \begin{bmatrix} B_{GG} & B_{GL} \\ B_{LG} & B_{LL} \end{bmatrix} \begin{bmatrix} \Delta V_G \\ \Delta V_L \end{bmatrix} \tag{14}$$

The sensitivity parameters between control and dependent variables can be derived based on equation (14) as fellows:

a) The load bus voltages related to control variables

● No changes in the reactive power at load-bus ($\Delta Q_L=0$)

The sensitivity parameters relating the changes in load-bus voltages due to the changes in generation-bus voltages are given as:

$$\Delta V_L = \begin{bmatrix} S_G^L \end{bmatrix} \Delta V_G \tag{15}$$

Where,

$$\begin{bmatrix} S_G^L \end{bmatrix} = -\begin{bmatrix} B_{LL} \end{bmatrix}^{-1} \begin{bmatrix} B_{LG} \end{bmatrix}$$

● No changes in generation voltages ($\Delta V_G=0$)

The sensitivity parameters relating to the changes in load-bus voltages due to the changes in switchable reactive power sources can be given as:

$$\Delta V_L = \begin{bmatrix} S_{SW}^L \end{bmatrix} \Delta Q_{SW} \tag{16}$$

Where,

$$\begin{bmatrix} S_{SW}^L \end{bmatrix} = -\begin{bmatrix} B_{LL} \end{bmatrix}^{-1} V_{SW}^{-1}$$

and, V_{SW} is the vector of bus voltages that connected to VAR sources.

b) Generation reactive power related to control variables

● The sensitivity parameters relating to the changes in generated reactive power due to the changes in generation-bus voltages can be written as:

$$\Delta Q_G /V_G = \begin{bmatrix} B_{GG} \end{bmatrix}\Delta V_G + \begin{bmatrix} B_{GL} \end{bmatrix}\Delta V_L \tag{17}$$

By substituting from equation (15) into (17), we obtain:

$$\Delta Q_G = \begin{bmatrix} S_G^G \end{bmatrix}\Delta V_G \tag{18}$$

Where,

$$\begin{bmatrix} S_G^G \end{bmatrix} = V_G \left\{ \begin{bmatrix} B_{GG} + [B_{GL}] \end{bmatrix} \begin{bmatrix} S_G^L \end{bmatrix} \right\}$$

● The sensitivity parameters relating to the changes in generated reactive power due to the changes in swtichable reactive power sources can be written as:

$$\Delta Q_G /V_G = \begin{bmatrix} B_{GG} \end{bmatrix}\begin{bmatrix} S_G^L \end{bmatrix}^{-1}\Delta V_L + \begin{bmatrix} B_{GL} \end{bmatrix}\Delta V_L \tag{19}$$

By substituting from equation (16) into (19), we get:

$$\Delta Q_G = \begin{bmatrix} S_{SW}^G \end{bmatrix}\Delta Q_{SW} \tag{20}$$

Where,

$$\begin{bmatrix} S_{SW}^G \end{bmatrix} = V_G \left\{ \begin{bmatrix} B_{GG} \end{bmatrix}\begin{bmatrix} S_G^L \end{bmatrix}^{-1} + \begin{bmatrix} B_{GL} \end{bmatrix}\begin{bmatrix} S_{SW}^L \end{bmatrix} \right\}$$

Now, the proposed sensitivity between the control and the dependent variables can be formulated based on equations (15), (16), (18) and (20) in a compact matrix form as:

$$\begin{bmatrix} \Delta V_L \\ \Delta Q_G \end{bmatrix} = \begin{bmatrix} S_G^L & S_{SW}^L \\ S_G^G & S_{SW}^G \end{bmatrix} \begin{bmatrix} \Delta V_G \\ \Delta Q_{SW} \end{bmatrix} \tag{21}$$

IV. ACO ALGORITHM

A random amount of pheromone is deposited in each rout after each ant completes it is tour, anther antes attract to the shortest route according to the probabilistic transition rule that depends on the amount of pheromone deposited and a heuristic guide function as equal to the inverse of the distance between beginning and ending of each route. The probabilistic transition rule of ant k to go from city i to city j can be expressed as:

$$P_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_q [\tau_{iq}(t)]^\alpha [\eta_{iq}(t)]^\beta} ; j,q \in N_i^k \tag{22}$$

Where, τ_{ij} is the pheromone trail deposited between city i and j by ant k, η_{ij} is the visibility or sight and equal to the inverse of the distance or the transition cost between city i and j ($\eta ij = 1/d_{ij}$). α and β are two parameters that influence the relative weight of pheromone trail and heuristic guide function, respectively. If $\alpha=0$, the closest cities are more likely to be selected that corresponding to a classical greedy algorithm. On the contrary, if $\beta=0$, the probability will be

depend on the pheromone trial only. These two parameters should be tuned with each other, q is the cities that will be visited after city i. N_r^k is a tabu list in memory of ant that recodes the cities which will be visited to avoid stagnations. After each tour is completed, a *local pheromone update* is determined by each ant depending on the route of each ant as in equation (23), after all ants attractive to the shortest route, a *global pheromone update* is considered to show the influence of the new addition deposits by the other ants that attractive to the best tour as shown in equation (24):

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\tau_\circ \qquad (23)$$

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \varepsilon\Delta\tau_{ij}(t) \qquad (24)$$

Where, $\tau_{ij}(t+1)$ is the pheromone after one tour or iteration, ρ is the pheromone evaporation constant, ε is the elite path weighting constant, $\tau_o = 1 / d_{ij}$ is the incremental value of pheromone of each ant. While, $\Delta\tau_{ij}$ is the amount of pheromone for elite path as:

$$\Delta\tau_{ij}(t) = 1 / d_{best} \qquad (25)$$

Where, d_{best} is the shortest tour distance.

V. ACO ALGORITHM FOR ORPD PROBLEM

ACO algorithm is applied to solve the ORPD problem as an optimization technique with control and dependent variable constraints where artificial ants travels in search space to find the shortest route that having the strongest pheromone trail and a minimum objective function. Our objective in this paper is to minimize the change in power losses as described in (1) with control variable constraints in (9) and (10), and dependent variable constraints in (11) and (12). So that, the heuristic guide function is the inverse of the individual change in losses of each ant that positioned in the reasonable limit of the control variable to the visibility of each ant. While, heuristic guide function of the problem is the inverse of the total change in losses at iteration $t +1$, as:

$$\eta(t+1) = 1 / \left[\sum_{G=1}^{NG} (\partial P_L / \partial V_G)\Delta V_G + \sum_{SW=1}^{NSW} (\partial P_L / \partial Q_{SW})\Delta Q_{SW} \right] \qquad (26)$$

In ACO algorithm, a search space creates with dimensions of stages on number of control variables and states or the randomly distributed values of control variables with in a reasonable threshold. Artificial ants leaves colony to search randomly in the search space based on the probability in (22) to complete a tour matrix that consists of the positions of ants with the same dimension of the search space. Then, tour matrix is applied on the objective function to find a heuristic guide function to find the best solution and update local and global pheromone to begin a next iteration. System parameters are adjusted by trail and error to find the best values of theses parameters.

The ACO algorithm can be applied to solve the ORPD problem using the following seven steps:

Step 1: Initialization

Insert the lower and upper boundaries of each control variable [$(\Delta V_G^{min}, \Delta V_G^{max})$ and $(\Delta Q_{SW}^{min}, \Delta Q_{SW}^{max})$], system parameters, and create a search space with a dimensions of number of control variables (ΔV_G, ΔQ_{SW}) and the length of randomly distributed values with the same dimension of the initial pheromone that contains elements with very small equal values to give all ants with the same chance of searching.

Step 2: Provide first position

Each ant is positioned on the initial state randomly within the reasonable range of each control variable in a search space with one ant in each control variable in the length of randomly distributed values.

Step 3: Transition rule

Each ant decide to visit a next position in the range of other control variables according to the probability transition rule in equation (22) that depends on the amount of pheromone deposited and the visibility that is the inverse of objective function (26). Where, the effect of pheromone and visibility on each other depends on the two parameters α and β.

Step 4: Local pheromone updating

Local updating pheromone is different from ant to other because each ant takes a different route. The initial pheromone of each ant is locally updated as in (23).

Step 5: Fitness function

After all ants attractive to the shortest path that having a strongest pheromone, the best solution of the objective function is obtained

Step 6: Global pheromone updating

Amount of pheromone on the best tour becomes the strongest due to attractive of ants for this path. Moreover, the pheromone on the other paths is evaporated in time.

Step 7: Program termination

The program will be terminated when the maximum iteration is reached or the best solution is obtained without the ants stagnations.

The proposed procedure steps are shown in Fig. 1.

VI. APPLICATIONS

A. Test Systems

The standard IEEE 14-bus system [7] and a real power system at West Delta network as a part of the Unified Egyptian Network (UEN) [8] are used to show the capability of ACO algorithm for solving solve the ORPD problem. The MVA base is taken 100 and the cost of power losses is assumed 0.07 E.P. /KWh while, the cost of reactive power is assumed 15 E.P. /KVar.
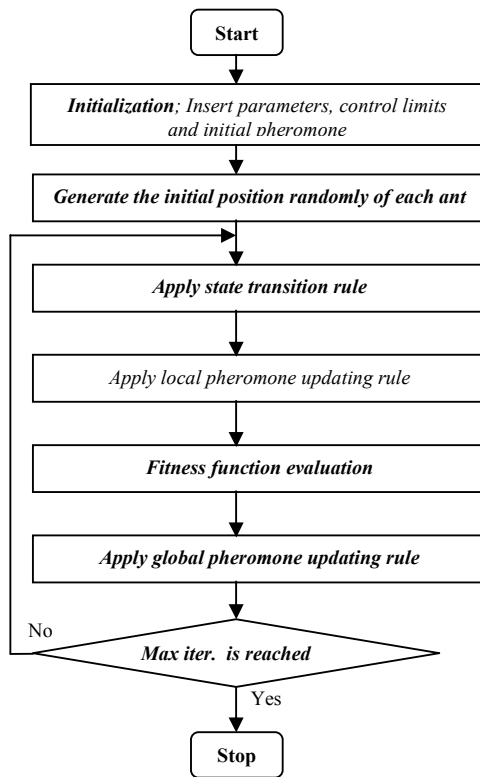
Fig. 1 Flow chart the proposed ACO algorithm

The results obtained are compared with those obtained using a conventional linear programming (LP), GA and PSO technique. The best values of ACO algorithm parameters are $\alpha = 1$, $\beta = 5$ $\rho = 0.5$ and $\varepsilon = 5$. The load flow is done using the Newton-Raphson load flow to get the values of power loss that are 13.593 and 22.811 MW for 14-bus and west delta system, respectively.

Figures 2 and 3 show the minimum, maximum limits and initial values of control and dependent variables for 14-bus test system and West Delta system.
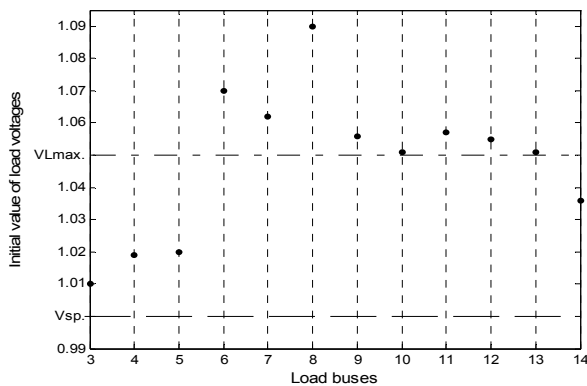

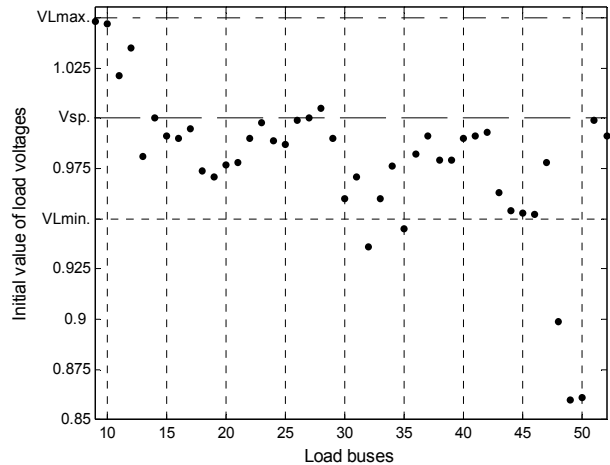Fig. 2 Initial values of load voltages for 14-bus system

Fig. 3 Initial values of load voltages for west delta system

B. Results and Comments

The results of the ACO algorithm are obtained using the MatLab code version 7.1 that setup on a Pentium 4, 3.0 GHz PC, 0.99 GB of RAM.

● *IEEE 14-bus test system*

Tables I, II and Fig. 4 show the ORPD using different optimization techniques. Table I shows the results of control variables (V_G and Q_{SW}) and dependent variables (Q_G). While, Fig. 4 shows the other dependent variables of load bus voltages (V_L) that eliminate the voltage violations using GA, PSO and ACO. While, buses 6 and 8 are still violated their limits using the conventional LP. Table II shows the results of power loss, cost of power loss (CPL), root mean square of load-bus voltage deviation with respect to the flat voltage (V.D.)$_{rms}$, reactive power reserve (RPR) and cost of the connected reactive power (CRP).

In Table II and Fig. 4, the ACO algorithm has minimum values of power loss, CPL, (V.D.)$_{rms}$ and CRP compared with other techniques. In addition, it has the maximum value of RPR compared with other techniques.

TABLE I
CONTROL AND DEPENDENT VARIABLES USING DIFFERENT
TECHNIQUES FOR 14-BUS SYSTEM.

Variables	LP	GA	PSO	ACO
V_{G1}	1.060	1.0059	1.0002	1.0000
V_{G2}	1.000	1.0042	1.0033	1.0002
Q_{SW9}	0.0773	0.0748	0.0847	0.0021
Q_{SW14}	0.0582	0.0471	0.0323	0.0015
Q_{G1}	-0.1919	-0.1825	-0.1745	-0.1593
Q_{G2}	0.46068	0.4563	0.4185	0.3862

TABLE II
A COMPARISON BETWEEN DIFFERENT OPTIMIZATION
TECHNIQUES FOR 14-BUS SYSTEM.

Variables	LP	GA	PSO	ACO
Power Loss (pu.)	0.1273	0.1124	0.1111	0.1094
CPL (EP)	891.1	786.69	777.7	765.44
(V.D.)rms	0.0414	0.0258	0.022	0.0137
RPR	0.2145	0.2281	0.233	0.253
CRP (EPx103)	203.25	182.85	175.5	145.5

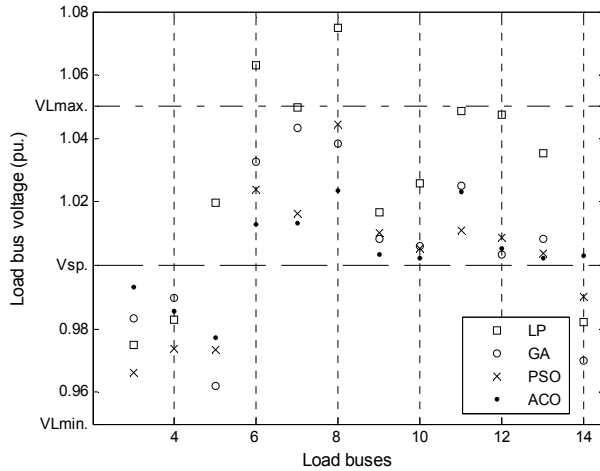Fig. 4 Load bus voltage using different techniques for 14-bus system

Fig. 5 Load bus voltage using different techniques for west delta system

- *West delta system*

Tables III, IV and Fig. 5 show the ORPD using different optimization techniques. Table III shows the results of control variables (V_G) and dependent variables (Q_G), while Fig. 5 shows the other dependent variables of load bus voltage (V_L). In Table IV, the ACO algorithm has minimum values of power loss with minimum cost and minimum voltage deviation compared with other techniques. Also, the load voltages based on ACO algorithm are the nearest to the flat voltage compared to the other techniques.

VII. CONCLUSION

This paper presents an ORPD based on ACO algorithm. The objective of the ORPD is to minimize the transmission line losses under control and dependent variable constraints which are proposed sensitivity parameters of reactive power that depend on a modification of Fast Decoupled Power Flow (FDPF) model. Three test systems have been used to show the capability of the proposed algorithm compared with other conventional LP, GA and PSO. The ACO algorithm leads to minimum power losses with minimizing of voltage deviation, cost of switchable reactive power and maximizing reactive power reserve compared to the other proposed algorithms. So, the proposed ACO algorithm gives more accurate and efficiently solution for ORPD problem.. Moreover, the proposed algorithm represents a potential tool to aid the power system operators in the on-line environment.

TABLE III
CONTROL AND DEPENDENT VARIABLES USING DIFFERENT
TECHNIQUES FOR WEST DELTA SYSTEM.

Variables	LP	GA	PSO	ACO
V_{G1}	1.0744	1.0753	1.0313	1.0385
V_{G2}	1.0159	1.0435	1.0478	0.9692
V_{G3}	0.9950	0.9872	0.9986	0.9695
V_{G4}	1.0019	1.0374	1.0241	0.9835
V_{G5}	1.0130	0.9638	1.0113	1.0465
V_{G6}	1.0084	1.0223	0.9794	0.9544
V_{G7}	1.0076	1.0125	1.0387	1.0182
V_{G8}	1.0066	0.9872	0.9686	0.9673
Q_{G1}	-0.9314	-0.4238	-0.1060	-0.6820
Q_{G2}	0.7907	0.4649	0.5300	0.1310
Q_{G3}	-0.7342	0.6398	0.9400	-0.8980
Q_{G4}	-1.7452	-1.2347	-1.4700	-1.2370
Q_{G5}	1.1691	0.9674	0.6300	0.8620
Q_{G6}	-1.4325	-1.3832	-1.0010	-0.7990
Q_{G7}	1.4185	1.4924	1.3620	1.0370
Q_{G8}	-2.0135	-0.1865	-0.5000	-0.2170

TABLE IV
A COMPARISON BETWEEN DIFFERENT OPTIMIZATION
TECHNIQUES FOR WEST DELTA SYSTEM

Variables	LP	GA	PSO	ACO
Power Loss (pu.)	0.2768	0.2116	0.1873	0.1698
CPL (EP)	1937.6	1481.2	1311.1	1188.6
(V.D.)rms	0.044	0.034	0.0317	0.024

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