CONSTRAINT OPTIMAL POWER FLOW BASED ON ANT COLONY OPTIMIZATION

Ali Qasim¹

* Dr. Layth Tawfeeq Al-Bahrani²

- 1) M.Sc. Student, Electrical Engineering Department, Collage of Engineering, Muatansiriayh University, Baghdad, Iraq
- 2) Electrical Engineering Department, Collage of Engineering, Muatansiriayh University, Baghdad, Iraq

Abstract: The Ant Colony Optimization ACO technique simulates the real ant colonies movements to find the best solution for huge optimization problems according to a group of agents called ants. In this article, the Ant Colony Optimization is used to solve a single objective function of Optimal Power Flow OPF problem with satisfied a set of the system constraints. ACO technique minimizes the objective function based on choosing an optimal control variables from their limits satisfying the state variables constraints. The performance of ACO in solving OPF problems has been demonstrated on the IEEE-30 bus system with different objective functions such as fuel cost minimization, voltage profile improvement and active power losses minimization. The results acquired through the simulation were good when compared with other optimization techniques reported in the literature. The outcomes suggest that this technique is effectively resolving the power system with vastly ranged network.

Keywords: *Constraint Optimal Power Flow, Ant Colony Optimization*

1. Introduction

The Optimal Power Flow OPF is one of the prevailing problems in power system [1]. Since the 1960s, the optimal power flow has been expressing a constrained economic power dispatch problem [2], it has been tested and studied for the purpose of obtaining an optimal

solution for minimizing an objective function through regulating power system control variables while still meeting the operational and physical constraints [3]. The control variables such as the generator real power, the generator bus magnitude voltage, the reactive power of shunt compensator and the tap ratios of transformer are selected from their limits of minimum and maximum values. The problem of the OPF can be solved into two techniques, the first optimization technique is well-known as conventional or classical technique such as linear programming, nonlinear programming, quadratic programming, newton method and interior point method,... etc. [4, 5]. These classical techniques provide a good result, but it suffer from many problem such as the high dimensionality, non-linearity, non-differentiability and the non-continuously that exist in the OPF. This type of optimization technique transition the optimal power flow into a complex problem and may be not able to present an optimal solution. In order to overcome some complications of the conventional optimization techniques, the second type of optimization techniques which are

*Corresponding Author: Laith1973a@gmail.com

renowned as the artificial intelligence optimization techniques has been used such as Genetic Algorithm GA, Artificial Neural Network ANN, Differential Evolution DE, Particle Swarm Optimization PSO, Artificial Bee Colony ABC and Ant Colony Optimization ACO,... etc. These optimization methods are inspired from the collective behaviors of animals and evolutionary algorithms [1]. The propose algorithm ACO is suggested to solve the constraint optimal power flow problem using the IEEE 30-bus test system to minimized the objective functions of OPF.

2. Optimal Power Flow (OPF) Problem Formulation

The OPF is the process of maximizing optimization with a number of objectives. The nature of the solution depends upon the accuracy of the studied mathematical model. Objectives must be tested for its practicality with potential solutions. Generally, OPF problem can be represented according to the following form:

$$\text{minimum } F(x, \mu) \quad (1)$$

$$g(x, \mu) = 0 \quad (2)$$

$$h(x, \mu) \leq 0 \quad (3)$$

$F(x, \mu)$ is the objective function; $g(x, \mu)$ is a function that represents the equality constraints; $h(x, \mu)$ is a function that represents the inequality constraints; x is the vector of dependent state variables; μ is the vector of independent control variables. The state variables vector x can be expressed as follows:

$$x = [P_{Gs}, V_{L1} \dots V_{NL}, Q_{G1} \dots Q_{GNG}] \quad (4)$$

P_{Gs} is the active power at slack generator; V_L is the voltage magnitude of the load bus; Q_G is the

reactive power output for all generation units; NL is number of load buses, NG is the number of generation units. The control variables vector μ can be expressed as follows:

$$\mu = \begin{bmatrix} P_{G2} \dots P_{GNG}, V_{G1} \dots V_{GNG}, \\ Q_{C1} \dots Q_{CNC}, T_1 \dots T_{NT} \end{bmatrix} \quad (5)$$

P_G is active power of the generator at PV buses; V_G is the voltage magnitude for all the generation units; Q_C is the shunt VAR compensation; T is the tap settings of the transformer; NC is the number of VAR compensators; NT is the number of transformers. The equality constraints are the load flow equations:

$$P_{Gi} - P_{Li} =$$

$$V_i \sum_{j=1}^{NB} V_j (G_{ij} \cos \theta_{ij} + G_{ij} \sin \theta_{ij}) \quad (6)$$

$$Q_{Gi} - Q_{Li} =$$

$$V_i \sum_{j=1}^{NB} V_j (G_{ij} \sin \theta_{ij} + G_{ij} \cos \theta_{ij}) \quad (7)$$

P_{Gi} is the generated active power at bus i ; Q_{Gi} is the generated reactive power at bus i ; P_{Li} is the active load demand at bus i ; Q_{Li} is the reactive load demand at bus i ; G_{ij} is the conductance between bus i and j ; B_{ij} is the susceptance between bus i and j ; NB is the total number of buses. The inequality constraints include two parts

- a- The inequality constraints of the control variables which consists of
- Upper and lower active power limit at PV bus i except the slack bus

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad i=2, \dots, NG \quad (8)$$

- Upper and lower voltage magnitude limit of generator i

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad i=1, 2, 3, \dots, NG \quad (9)$$

- Upper and lower limit of shunt VAR compensator

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \quad i=1, 2, 3, \dots, NC \quad (10)$$

- Upper and lower tap settings limit of transformer i

$$T_i^{min} \leq T_i \leq T_i^{max} \quad i=1, 2, 3, \dots, NT \quad (11)$$

- b- The inequality constraints of the control variables which consists of

- Upper and lower reactive power limit of generator i

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad i=1, 2, \dots, NG \quad (12)$$

- Upper and lower voltage limit at load bus i

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max} \quad i=1, 2, \dots, NL \quad (13)$$

- Upper and lower active power of the slack generator s

$$P_{Gs}^{min} \leq P_{Gs} \leq P_{Gs}^{max} \quad (14)$$

3. Objective Functions

Different Objective Functions of Optimal Power Flow have been used in this article to illustrate the efficiency of the proposed technique of Ant Colony Optimization. The various cases of objective functions are given as follows:

3.1. Case 1: Generation fuel cost

The total system fuel cost is modelled as the sum of the cost function of each generator. The generator fuel cost curves are modelled with smooth quadratic functions and measured by the unit \$/h as shown in the equation (15).

$$Cost = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (15)$$

where NG is the number of thermal units, P_{Gi} is the active power generation at unit i and a_i , b_i , c_i are the cost coefficients of the i th generator.

3.2. Case 2: Voltage profile improvement

The second objective function is to minimize the voltage deviation at the load buses from a specified voltage, which can be expressed as follows:

$$VD = \sum_{i=1}^{NPQ} |V_i - 1| \quad (16)$$

Where VD is the total voltage deviation at the load buses; NPQ is the number of load buses and V_i is the magnitude voltage at bus i .

3.3. Case 3: Active power transmission losses

In this case the required objective function is to minimize the active power transmission losses which is formulated as follows:

$$P_{loss} = \sum_{k=1}^{NTL} G_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \quad (17)$$

where, G_{ij} the mutual conductance between bus i and bus j respectively; V_i and V_j representing the voltage magnitude at bus i and bus j respectively; NTL is the number of transmission lines and θ_{ij} is voltage angle difference between buses voltages i and j .

4. Mechanism of Ant Colony Optimization

Ant Colony Optimization imitates the behavior of real ant. Real ants can find the shortest possible

route (path) between a food source and their nest by depositing the pheromone material. The pheromone material is a chemical substance produced by the ants evaporates with the time. It acts as a way of communication between the ants. This mechanism allowing the ants to choose the shortest possible route to search the food for the next movement. The pathway that has the highest pheromone concentration will be end up the target route [6, 7].

5. State Transition Rule

The ant choose the next node from the states of the second stage according to the state transition rule $P(r, s)$ as shown in equation (18)

$$P_{(r,s)}^k = \begin{cases} \frac{\tau_{(r,s)}^{\alpha_1} \times \gamma_{(r,s)}^{\alpha_2}}{\sum \tau_{(r,s)}^{\alpha_1} \times \gamma_{(r,s)}^{\alpha_2}} & r, s \in T \\ 0 & , otherwise \end{cases} \quad (18)$$

$\tau_{(r,s)}$ is the pheromone deposited (intensity of pheromone) between nodes r and s ; r is the previously node; s is the currently node; $\gamma_{(r,s)}$ is the heuristic information which is the inverse of the distance between node r and s ; α_1, α_2 are constants to control the influence of $\tau_{(r,s)}, \gamma_{(r,s)}$ respectively; k is the ant number; T is the set of paths that ant k has not visited. The probability of selection a particular path $P_{(r,s)}^k$ increases with the value of the related pheromone trail $\tau_{(r,s)}$ and of the heuristic information value $\gamma_{(r,s)}$.

6. Local updating rule

When constructing a solution (implemented path), the ants will utilize a local pheromone update rule. This local pheromone is applied instantly after crossing the edge (r, s) during the making of the path of control variables shown in equation (5). In others words, this update is

satisfied after finishing the vector of control variables for a specified objective function.

$$\tau_{(r,s)} = \rho \tau_{(r,s)} + \tau_{(r,s)}^k \quad (19)$$

$$\Delta \tau_{(r,s)}^k = 1/(CP \times OF) \quad (20)$$

where $(0 < \rho \leq 1)$ is the persistence of the pheromone trail; $\Delta \tau_{(r,s)}^k$ is the amount of pheromone ant k deposits on the path it has visited; CP is a larger positive constant and OF is the objective function [8].

7. Global update rule

Each tours (path) of ant represents a vector of control variables which has a specific objective function. After all ants complete their tours (path), the solution of population for the objective function is determined. The pheromone trails (r,s) of the best ant tour that has minimum objective function is updated according to the global updating rule in equation (18)

$$\tau_{(r,s)} = (1 - \rho)\tau_{(r,s)} + \rho\Delta\tau_{(r,s)}^{best} \quad (21)$$

$$\Delta\tau_{(r,s)}^{bs} = 1/(OF)^{best} \quad (22)$$

where $(OF)^{best}$ is best objective function based on best tour; The equations (21, 22) show the pheromone trail update for each $(r,s) \in L^{best}$, where L^{best} is best tour found since the start of algorithm. Both of evaporation and new deposit of pheromone are applies to L^{best} edges [9].

8. Ant Colony Optimization ACO in Constrained Optimal Power Flow

In this application, the power system constraints are achieved by integration the control variables settings between the maximum and minimum values keeping the state variables in their limits.

Figure (1) describes the ACO technique from the nest to the destination to find the optimal path for a specific objective function. The control variables are represented by the stages ($i=1, \dots, n$) while the candidate values between the minimum and maximum limits of each stage are represented by a set of the state nodes ($j=1, \dots, D$). The artificial ants will start to move from the nest (home colony) and it will pass through each stage (control variables), then stop at the destination (objective function). The ant chooses the state of each stage to complete one path. As example, the ant chooses the vector of control variables $[X_{12}, X_{23}, X_{33}, X_{41}, X_{52}, \dots, X_{n2}]$ to complete one path for specific objective function.

Figure 1. ACO for the OPF problem

9. The steps of the ACO algorithm

Step 1: Initialization

Initialize the population of the Ant Colony Optimization where the number of population is equal to the number of ants. Each vector of population is represent by a path of the ant, where each path of ant is equal to vector of control variable. The population is equal to a set of control variables.

Step 2: Create the first node

The first node is chosen randomly from the states for the first stage (first stage represents first control variable)

Step 3: Apply state transition rule

The state transition rule $P_{(r,s)}$ in equation (18) is applied for each state to select the next node, it is applied through considering the previously selected state (r) in step 2. The path to be chosen is determined based on the following points:

- The roulette-wheel selection procedure is applied to choose a particular path for each ant (k) as shown in the step (b, c, d) below:
- Generate a random number in the range $(0,1)$. This number is different for each ant.
- Find the ranges of cumulative probability connected with different paths based on equation 15.
- Compare the cumulative probability range in point (c) with the random number generated in point b, if it is larger than the random number, this means that the respective state (s) can be accepted as a path for the ant. Otherwise, it will be ignored.

This selection will be repeat for all paths (s) from the current control variable state.

Step 4: Solution for each ant

After the paths have been determined for all the ants. The total objective function traversed by each ant must be calculated, this total objective function is used to update the pheromone.

Step 5: The pheromone update rule

Update the local and global pheromone level using the equations (19, 20) and (21, 22) respectively.

Step 6: Termination condition

The ACO algorithm stops the iteration after the maximum number of iterations are finished and the tour is completed by all the ants. After the termination condition has been satisfied and all

the ants taken the tour, the best solutions provided by the ants are presented.

10. The application and result

The IEEE 30 bus system in figure 2 has been used to test different single objective optimal power flow problem based on the Ant Colony Optimization technique. This system has 6 generators at buses 1, 2, 5, 8, 11 and 13 with four transformers at lines 4-12, 6-9, 6-10 and 28-27, also this system has nine shunt VAR compensation at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. Therefore, this system has 24 control variables. Table 1 represent the cost coefficients of the generation units.

Figure 2. IEEE-30 Bus System

Table 1. Generator cost coefficients

Unit number (<i>i</i>)	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MW ² h)
1	0	2.00	0.00375
2	0	1.75	0.0175
5	0	1.00	0.0625
8	0	3.25	0.0083
11	0	3.00	0.0250
13	0	3.00	0.0250

Table 2 shows the optimal setting of the Control Variables (C.V) with its minimum objective functions (case1: fuel cost (\$/h), case2: voltage deviation (pu) and case3: active power losses (MW) using the propose algorithm of the Ant Colony Optimization ACO technique.

Table 2. Control Variables(C.V) for the three cases of objective function

C.V	Mn.	Mx.	Initial	Case1	Case2	Case3
P_{G2}	20	80	80	48.9	61.44	68.09
P_{G5}	15	50	50	22.68	26.71	48.83
P_{G8}	10	35	20	19.59	15.47	34.87
P_{G11}	10	30	20	10.7	26.96	26.35
P_{G13}	12	40	20	13.17	36.37	38.92
V_{G1}	0.95	1.1	1.05	1.085	1.015	1.086
V_{G2}	0.95	1.1	1.04	1.064	1.006	1.078
V_{G5}	0.95	1.1	1.01	1.047	1.016	1.068
V_{G8}	0.95	1.1	1.01	1.035	1.009	1.062
V_{G11}	0.95	1.1	1.05	1.065	1.083	1.097
V_{G13}	0.95	1.1	1.05	1.056	0.995	1.091
T_{4-12}	0.9	1.1	1.078	1.058	0.945	1.016
T_{6-9}	0.9	1.1	1.069	1.091	1.079	1.048
T_{6-10}	0.9	1.1	1.032	0.962	0.925	0.973
T_{28-2}	0.9	1.1	1.068	1.043	0.947	0.981
Q_{C10}	0	5	0	2.044	2.553	4.674
Q_{C12}	0	5	0	2.827	0.619	0.244
Q_{C15}	0	5	0	4.798	3.673	2.376
Q_{C15}	0	5	0	4.595	4.398	4.183
Q_{C17}	0	5	0	4.940	4.814	4.296
Q_{C20}	0	5	0	1.416	2.488	2.318
Q_{C21}	0	5	0	0.038	4.774	3.837
Q_{C23}	0	5	0	4.308	3.075	2.541
Q_{C29}	0	5	0	4.359	0.558	1.440
Objective function						
Case 1: Fuel Cost (\$/h)			902.0	801.4	843.6	930.4
Case 2: Voltage deviation (pu)			1.154	0.429	0.119	1.187
Case 3: Power losses (MW)			5.839	9.221	7.376	3.417

According to Table 2, the total fuel cost is substantially decreased from initial value of 902.0 \$/h to optimal value of 801.4 \$/h with reduction of (11.15 %). The voltage deviation decreasing from initial value of 1.1547 pu to optimal value of 0.119 pu with a reduction of 89.69%. The active

power transmission line losses is significantly decreased by (41.48 %) from initial value of 5.839 MW to optimal value of 3.417 MW. The variation of the three objective functions (fuel cost, voltage deviation and active lower losses) with number of iteration are illustrated in the Figures 3, 4 and 5 respectively.

Figure 3. Fuel Cost (\$/h) with iteration number

Figure 4. Voltage deviation (pu) with iteration number

Figure 5. Active losses (MW) with iteration number

Table 3 shows the state variables of the generators reactive power and the active power of the slack generator which they not exceed their limits after applying the ACO technique to solve the OPF problem. Therefore, the condition of the constraint OPF are satisfied.

Table 3. Generators reactive power constraint and slack active power constraint

Units	Min	Max	Case1	Case2	Case3
1	-20	200	10.5	-8.0	3.54
3	-20	100	12.51	-1.98	9.74
5	-15	80	42.92	60.15	36.38
8	-15	60	17.07	54.89	24.52
11	-10	50	29.79	42.39	24.44
13	-15	60	25.99	-10.15	20.17
slack active power	50	200	177.4	123.81	69.760

Also the constraint of the state variable of the load voltage after applying ACO technique to solve the OPF problem are within the minimum and maximum limits (0.9 and 1.1 respectively) as shown in the Figure 7.

Figure 7. Magnitude voltage in pu of IEEE 30 bus

The propose algorithm gives good result when compare with other optimization techniques used the same data and test system of IEEE 30 bus as shown in Tables (4, 5 and 6).

Table 4. Comparison of voltage deviation VD with other optimization techniques

Ref.	Optimization techniques	VD (pu)
[19]	Differential Evolution	0.19
[20]	Particle Swarm Optimization	0.1334
[20]	Moth-flame Algorithm	0.0976
[21]	Black-hole-Based Optimization	0.1262
propose method	Ant Colony Optimization	0.1194

Table 5. Comparison of active power losses P_{loss} with other optimization technique

Ref.	Optimization techniques	P_{loss} (MW)
[22]	conventional interior point	5.101
[22]	Particle Swarm Optimization	5.092
[19]	Differential Evolution	4.760
[23]	Differential Evolution	4.720
[24]	Real coded Genetic Algorithm	4.501
[14]	Flower Pollination Algorithm	3.5661
[21]	black-hole-Based Optimization	3.503
propose method	Ant Colony Optimization	3.4171

Table 6. Comparison of fuel cost with other optimization techniques

Ref.	Optimization techniques	Fuel cost (\$/h)
[11]	Gradient	804.85
[12]	Ant Colony Optimization	803.12
[13]	Differential Evolution	803.05
[13]	Imperialistic Competitive	802.88
[14]	Flower Pollination Algorithm	802.79
[15]	Improved PSO	802.63
[15]	Evolutionary Programming	802.62
[16]	modified differential evolution	802.37
[17]	modified shuffle frog leaping	802.28
[18]	Particle Swarm Optimization	801.66
propose method	Ant Colony Optimization	801.43

This minimization of the objective function based on ACO technique indicates the effectiveness of the proposed technique to solve OPF problem

11. Conclusion

This article used the Ant Colony Optimization ACO to solve the Optimal Power Flow OPF problems. One test system and three cases of

objective functions were tested to determine the efficiency of the suggested algorithm. The proposed algorithm chooses the optimal control variables to minimize these different Objective functions (fuel cost, voltage deviation and active power losses), while satisfying different types of constraints. On the IEEE 30-bus test system, the practicability of the expected approach has been checked. The acquired outcomes from this technique were good when compared with other optimization techniques that used to solve the OPF problem in the literature of this article. It proved to be effective, accurate, successful, acceptable solutions and has low implementation time in solving optimal power flow problem. The proposed algorithm ACO was executed step by step using the programming of M file in the MATLAB software.

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Conflict of interest

The authors identify and declare that the publication of this article cause no conflict of interest.

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