



Collective Intelligence for Optimal Power Flow Solution Using Ant Colony Optimization

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Abstract

This paper presents the performance ant collective intelligence efficiency for electrical network. Solutions for Optimal Power Flow (OPF) problem of a power system deliberate via an ant colony optimization metaheuristic method. The objective is to minimize the total fuel cost of thermal generating units and also conserve an acceptable system performance in terms of limits on generator real and reactive power outputs, bus voltages, shunt capacitors/reactors, transformers tap-setting and power flow of transmission lines. Simulation results on the IEEE 30-bus electrical network show that the ant colony optimization method converges quickly to the global optimum.

Keywords

Collective Intelligence; Ant Colony Optimization; Optimal Power Flow; Power Systems; Metaheuristic; IEEE tests systems.

Introduction

The optimal power flow has been frequently solved using classical optimization methods. The OPF has been usually considered as the minimization of an objective function representing the generation cost and/or the transmission loss. The constraints involved are the physical laws governing the power generation-transmission systems and the operating limitations of the equipment.

Effective optimal power flow is limited by the high dimensionality of power systems and the incomplete domain dependent knowledge of power system engineers. The first limitation is addressed by numerical optimization procedures based on successive linearization using the first and the second derivatives of objective functions and their constraints as the search directions or by linear programming solutions to imprecise models [1, 2]. The advantages of such methods are in their mathematical underpinnings, but disadvantages exist also in the sensitivity to problem formulation, algorithm selection and usually converge to local minima [3]. The second limitation, incomplete domain knowledge, precludes also the reliable use of expert systems where rule completeness is not possible. In the evolutionary and adaptive algorithms one of the most recent is the Ant Colony Optimization (ACO) computational paradigm introduced by Marco Dorigo in his Ph.D. thesis in 1992 [4], and expanded it in his further work, as summarized in [5, 6, 7].

ACO offer a new powerful approach to these optimization problems made possible by the increasing availability of high performance computers at relatively low costs.

As the name suggests, these algorithms have been inspired in the real ant colonies behavior. When searching for food, ants initially explore the area surrounding their nest in a random manner. As soon as an ant finds a food source, it evaluates quantity and quality of the food and carries some of the found food to the nest. During the return trip, the ant deposits a chemical pheromone trail on the ground. The quantity of pheromone deposited, which may depend on the quantity and quality of the food, will guide other ants to the food source. The indirect communication between the ants via the pheromone trails allows them to find shortest paths between their nest and food sources. This functionality of real ant colonies is exploited in artificial ant colonies in order to solve global optimization searching problems when the closed-form optimization technique cannot be applied.



ACO is characterized by the use of a (parameterized) probabilistic model that is used to generate solutions to the problem under consideration. The probabilistic model is called the pheromone model. The pheromone model consists of a set of model parameters, which are called the pheromone trail parameters. The pheromone trail parameters have values, called pheromone values. At run-time, ACO algorithms try to update the pheromone values in such a way that the probability to generate high-quality solutions increases over time. The pheromone values are updated using previously generated solutions. The update aims to concentrate the search in regions of the search space containing high-quality solutions. In particular, the reinforcement of solution components depending on the solution quality is an important ingredient of ACO algorithms. It implicitly assumes that good solutions consist of good solution components. To learn which components contribute to good solutions can help to assemble them into better solutions.

In general, the ACO approach attempts to solve an optimization problem by repeating the following two steps.

- 1) Candidate solutions are constructed using a pheromone model; that is, a parameterized probability distribution over the solution space;
- 2) The candidate solutions are used to modify the pheromone values in a way that is deemed to bias future sampling toward high-quality solutions.

ACO methods have been successfully applied to diverse combinatorial optimization problems including travelling salesman [8, 9], quadratic assignment [10, 11], vehicle routing [12, 13, 14], telecommunication networks [15], graph colouring [16], constraint satisfaction [17], Hamiltonian graphs [18], and scheduling [19, 20, 21].

In this paper, we showed the application of the ant colony optimization algorithms in the Optimal Power Flow (OPF) on the IEEE 30-bus Electrical Network.

The ACO is more likely to converge toward the global solution because it, simultaneously, evaluates many points in the parameter space. It does not need to assume that the search space is differentiable or continuous. To accelerate the processes of ACO-OPF, the controllable variables are decomposed to active constraints that effect directly the cost function are included in the ACO process and passive constraints which are updating using a conventional load flow program, only, one time after the convergence on the ACO-OPF. The slack bus parameter would be recalculated in the load flow process to take the effect of the passive constraints.

The algorithm was developed in an object oriented fashion, in the MATLAB environment programming (R2008a, v7.6).

Problem Formulation

The standard OPF problem can be written in the following form:

$$\begin{cases} \min \{F(x)\} \\ \text{Subject to : } h(x) = 0 \\ \text{and : } g(x) \geq 0 \end{cases} \quad (1)$$

where $F(x)$ the objective function, $h(x)$ represents the equality constraints, $g(x)$ represents the inequality constraints and x is the vector of the control variables, that is those which can be varied by a control center operator (generated active and reactive powers, generation bus voltage magnitudes, transformers taps ... etc.).

The essence of the optimal power flow problem resides in reducing the objective function and simultaneously satisfying the load flow equations (equality constraints) without violating the inequality constraints.

Objective Function

The most commonly used objective in the OPF problem formulation is the minimization of the total cost of real power generation. The individual costs of each generating unit are assumed to be function, only of active power generation and are represented by quadratic curves of second order. The objective function for the entire power System can then be written as the sum of the quadratic cost model at each generator:

$$F(x) = \sum_{i=1}^{ng} (a_i + b_i P_{g_i} + c_i P_{g_i}^2) \quad (2)$$

Where ng is the number of generation including the slack bus. P_{g_i} is the generated active power at bus i .

$a_i - b_i$ and c_i are the unit costs curve for i^{th} generator.

Types of Equality Constraints

While minimizing the cost function, it is necessary to make sure that the generation still supplies the load demands P_d plus losses in transmission lines. Usually the power flow equations are used as equality constraints:

$$\begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix} = \begin{bmatrix} P_i(V, \theta) - (Pg_i - Pd_i) \\ Q_i(V, \theta) - (Qg_i - Qd_i) \end{bmatrix} = 0 \quad (3)$$

Where active and reactive power injection at bus i are defined in the following equation:

$$P_i(V, \theta) = \sum_{j=1}^{nbus} V_i V_j (g_{ij} \cos \theta_{ij} + b_{ij} \sin \theta_{ij}); \quad i = 2, nbus \quad (4)$$

$$Q_i(V, \theta) = \sum_{j=1}^{nbus} V_i V_j (g_{ij} \sin \theta_{ij} - b_{ij} \cos \theta_{ij}); \quad i = npv + 1, nbus \quad (5)$$

Where g_{ij} is the conductance, b_{ij} is the susceptance, V_i is voltage magnitude at the bus i and θ_{ij} is the bus voltage phase angle.

Types of Inequality Constraints

The inequality constraints of the OPF reflect the limits on physical devices in the power system as well as the limits created to ensure system security. The most usual types of inequality constraints are upper bus voltage limits at generations and load buses, lower bus voltage limits at load buses, var. limits at generation buses, maximum active power limits corresponding to lower limits at some generators, maximum line loading limits and limits on tap setting of TCULs and phase shifter. The inequality constraints on the problem variables considered include:

Upper and lower bounds on the active generations at generator buses:

$$Pg_i^{min} \leq Pg_i \leq Pg_i^{max}, \quad i = 1, ng \quad (6)$$

• Upper and lower bounds on the reactive power generations at generator buses and reactive power injection at buses with VAR compensation:

$$Qg_i^{min} \leq Qg_i \leq Qg_i^{max}, \quad i = 1, npv \quad (7)$$

• Upper and lower bounds on the voltage magnitude at the all buses:

$$Vg_i^{min} \leq Vg_i \leq Vg_i^{max}, \quad i = 1, nbus \quad (8)$$

• Upper and lower bounds on the bus voltage phase angles:

$$\theta g_i^{min} \leq \theta g_i \leq \theta g_i^{max}, \quad i = 1, nbus \quad (9)$$

• Upper and lower bounds on branch MW/MVAR/MVA flows may come from thermal ratings of conductors, or they may be set to a level due to system stability concerns:

$$|S_{ij}|^2 \leq S \max_{ij}^2 \quad (10)$$

It can be seen that the generalized objective function F is a non-linear, the number of the equality and inequality constraints increase with the size of the power distribution systems. Applications of a conventional optimization technique such as the gradient-based algorithms to a large power distribution system with a very non-linear objective functions and great number of constraints are not good enough to solve this problem. Because it depend on the existence of the first and the second derivatives of the objective function and on the well computing of these derivative in large search space.

Ant Colony Optimization in Optimal Power Flow

Description of ant colony optimization method

In the ant colony optimization (ACO), a colony of artificial ants cooperates in finding good solutions to difficult optimization problems. Cooperation is a key design component of ACO algorithms: The choice is to allocate the computational resources to a set of relatively simple agents (artificial ants) that communicate indirectly by stigmergy. Good solutions are an emergent property of the agent's cooperative interaction.

Artificial ants have a double nature. On the one hand, they are an abstraction of those behavioral traits of real ants which seemed to be at the heart of the shortest path finding behavior observed in real ant colonies. On the other hand, they have been enriched with some capabilities which do not find a natural counterpart. In fact, we want ant colony optimization to be an engineering approach to the design and implementation of software Systems for the solution of difficult optimization problems. It is therefore reasonable to give artificial ants some capabilities that, although not corresponding to any capacity of their real ant's counterparts, make them more effective and efficient.

The objective function to be minimized, as in the traveling salesman problem, is:

$$F(\pi) = \sum_{i=1}^{n-1} tc(S_{\pi(i)}, S_{\pi(i+1)}) + tc(S_{\pi(n)}, S_{\pi(1)}) \quad (11)$$

where $tc(S_i, S_j)$ is the transition cost between state i and j , and $\pi(i)$ for $i = 1, \dots, n$ defines a permutation.

The number of ants is m and given by:

$$m = \sum_{i=1}^n b(i) \quad (12)$$

where $bi(t)$ is the number of the ants in state i at time t .

Each ant generates a complete tour by choosing the cities according to a probabilistic state rule. Mathematically, the probability with which ant k in city r chooses to move to the city s is [22]:

$$P_k(r,s) = \begin{cases} \frac{\left(\sum_{i=1}^r [\gamma^{r-i} \cdot \tau(i,s)]\right)^\alpha \cdot [\eta(r,s)]^\beta}{\sum_{v \in J_k(r)} \left(\left(\sum_{i=1}^r [\gamma^{r-i} \cdot \tau(i,v)]\right)^\alpha \cdot [\eta(r,v)]^\beta\right)} & \text{if } s \in J_k(r) \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where τ is the pheromone, η is the visibility which is the inverse of the distance $\delta(r,s)$, $J_k(r)$ is the set of cities that remain to be visited by ant k positioned on city r , α and β are two coefficients which make the pheromone information or the visibility information more important with respect to one another and the parameter $\gamma > 0$ determines the relative influence of pheromone values corresponding to earlier decisions, preceding places in the permutation.

A value $\gamma = 1$ results in unweighted summation evaluation, every τ_{ir} , $i \leq r$ is given the same influence. A value $\gamma < 1$ ($\gamma > 1$) gives pheromone values corresponding to earlier decisions less (respectively more) influence.

The best solutions found so far and in the current generation are used to update the pheromone information. However, before that, some portion of pheromone is evaporated according to:

$$\tau_{rs} = (1 - \rho)\tau_{rs} \quad (14)$$

Where ρ is the evaporation rate with $0 \leq \rho < 1$ and $(1-\rho)$ is the trail persistence. The reason for this is that old pheromone should not have too strong an influence on the future.

Let $\tau_{rs}(t)$ be the intensity of trail on edge (r,s) at time t . Each ant at time t chooses the next city, where it will be at time $t+1$. Therefore, after each cycle, after each ant has determined a tour, the pheromone trail is updated using the founded solutions according to the following formula:

$$\tau_{rs}(t+n) = \rho \cdot \tau_{rs}(t) + \sum_{K=1}^m \Delta\tau_{rs}^{(k)} \quad (15)$$

where $\Delta\tau_{rs}^{(k)}$ is the contribution of the ant k to the pheromone trail between cities r and s . Usually,

$$\Delta\tau_{rs}^{(k)} = \begin{cases} \frac{Q_0}{L_k} & \text{if } (r,s) \in \text{to the tour of ant } k \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

Where Q_0 is a constant related to the amount of pheromone laid by ants and L_k is the tour length of the k -th ant.

The process is then iterated and the algorithm runs until some stopping criterion is met, a certain number of generations have been done or the average quality of the solution found by the ants of a generation has not changed for several generations.

ACO Applied to Optimal Power Flow

Our objective is to minimize the objective function of the OPF defined by (2), using into account the equality constraints (3), and the inequality constraints (6)-(10). The cost function implemented in ACO is defined as:

$$F(x) = \sum_{i=1}^{ng} (a_i + b_i P_{g_i} + c_i P_{g_i}^2); P_{g_i}^{min} \leq P_{g_i} \leq P_{g_i}^{max}; \quad i = 1, ng \quad (17)$$

Where, only equations (2) and (6) are considered.

The search of the optimal parameters set is performed using into account a part of the equality constraints (3) which present the active power transmission losses (P_L) to be deal with in feasible region.

The search of the optimal control vector is performed using into account the real power flow equation defined by (4) which present the system transmission losses (P_L). These losses can be approximated in terms of B-coefficients as [23]:

$$Pf = \left(I - \frac{\partial P_L}{\partial Pg} \right)^{-1} \quad (18)$$

These losses are represented as a penalty vector given by:

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_{g_i} \cdot B_{ij} \cdot P_{g_j} \quad (19)$$

The transmission loss of a power System P_L can be calculated by the B-Coefficients method [24] and given by:

$$P_L = Pg^T \cdot B \cdot Pg + Pg^T \cdot B_0 + B_{00} \quad (20)$$

where Pg is a ng -dimensional column vector of the generator power of the units, Pg^T is the associate matrix of Pg , B is an $ng \times ng$ coefficients matrix, B_0 is an ng -dimensional coefficient column vector and B_{00} is a coefficient.

Our objective is to search (Pg) set in their admissible limits to achieve the optimization problem of OPF. At initialization phase, (Pg) is selected randomly between Pg_i^{min} and Pg_i^{max} .

The use of penalty functions in many OPF solutions techniques to handle inequality constraints can lead to convergence problem due to the distortion of the solution surface. In this method only the active power of generators are used in the cost function. And the inequality constraints are scheduled in the load flow process. Because the essence of this idea is that the constraints are partitioned in two types of constraints, active constraints are checked using the ACO-OPF procedure and the reactive constraints are updating using an efficient Newton-Raphson Load flow procedure.

After the search goal is achieved, or an allowable generation is attained by the ACO algorithm. It is required to performing a load flow solution in order to make fine adjustments on the optimum values obtained from the ACO-OPF procedure. This will provide updated voltages, angles and transformer taps and points out generators having exceeded reactive limits. To determining ail reactive power of ail generators and to determine active power that it should be given by the slack generator using into account the deferent reactive constraints. Examples of reactive constraints are the min and the max reactive rate of the generators buses and the min and max of the voltage levels of all buses. All these require a fast and robust load flow program with best convergence properties. The developed load flow process is based upon the full Newton-Raphson algorithm using the optimal multiplier technique [25, 26].

There are few parameters that to be set for the ant algorithm; these parameters are: ρ the evaporation rate, m the numbers of ants in the colony, α and β two coefficients. In the OPF case these values were obtained by a preliminary optimization phase, in which we found that the experimental optimal values of the parameters were largely independent of the problem. The initial pheromone τ_0 is given by $\tau_0 = (ng \cdot L) - 1$ where L is the tour length produced by the nearest neighbor heuristic. The number of ants used is $m=20$. Regarding their initial positioning, ants are placed randomly, with at most one ant in each generator unit.

A local improvement method suggested by Johnson & McGeoch [27] called the restricted 3-opt method has been adapted for use in the ACO. It involves successive arc-exchanges in an attempt to improve a candidate solution. But we choose a limited number of exchanges in order to avoid over-long computation times. The local search is applied once the solution is built and the results of this phase are used to update the pheromone trails.

The ACO algorithm applied to OPF can be described in the following steps.

Step 1: Input parameters of system, and specify the lower and upper boundaries of each control variable.

Step 2: Each ant is positioned on the initial state which is generated randomly within the feasible region. The initial control vector is generated randomly from a reasonable range in each dimension by setting the elements of Pg as $Pg = U(Pg^{min}, Pg^{max})$ where $U(Pg^{min}, Pg^{max})$ denotes the outcome of a uniformly distributed random variable ranging over the given lower bounded value and upper bounded values of the active power outputs of generators.

Step 3: In this step, according to the objective function in (17), their performance will be weighed as fitness value for each ant. The direct influence of this fitness value depends upon the level of pheromone quantity adding to the particular directions the ants have selected.

Step 4: the ants are dispatched based on the level of the pheromone intensity and visibility.

Step 5: To each ant, employ the Newton-Raphson method to calculate power flow in order to make fine adjustments on the optimum values obtained in step 4. This will provide updated voltages, angles and points out generators having exceeded reactive limits.

Application Study, Results and Discussion

The ACO-OPF is coded in MATLAB environment version 7.6 (R2008a), and run using an Intel Pentium 4, core duo 1.87 GHz PC with 2 Go DDRAM-II- and 2 Mo cache memory. All computations use real float point precision without rounding or truncating values. More than 6 small-sized test cases were used to demonstrate the performance of the proposed algorithm. Consistently acceptable results were observed.

The ACO-OPF method has been applied on the network test IEEE 30 buses that represent a portion of the American electric power system (the Midwestern, USA) for December 1961. This electric network is constituted of 30 buses and 6 generators (at the buses $N_b = 1, 2, 5, 8, 11, \text{ and } 13$) injecting their powers for a system nourishing 20 loads

through 41 lines of transportation (Show in Fig 1). The base voltage for every bus is of 135 kV.

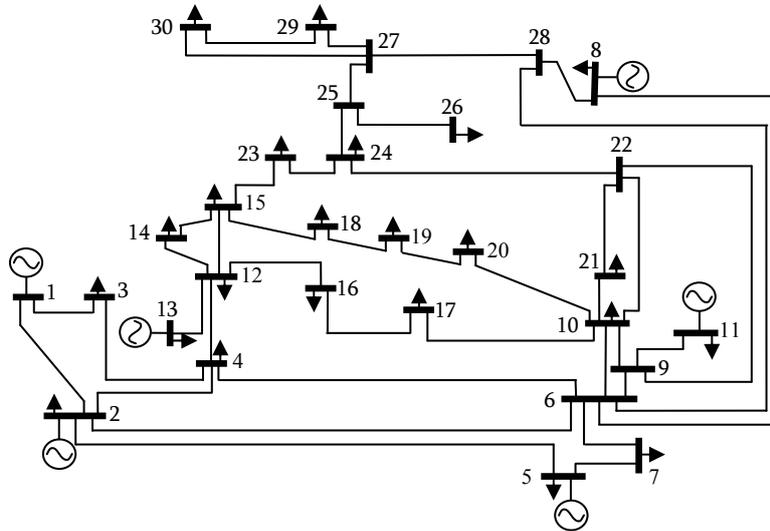


Figure 1. Topology of the IEEE 30-bus

Table 1 show the coefficients of the quadratic functions of cost and the limits min and max of the actives powers, the technical and economic parameters of the six generators of the IEEE 30-bus electrical network.

Table 1. Generators parameters of the IEEE 30-bus Electrical Network

Bus Number	Pg_i^{min} [MW]	Pg_i^{max} [MW]	a [\$/hr]	b [\$/MWhr]	c [\$/MW ² hr]
Bus 1	50	200	0	2.00	$37.5 \cdot 10^{-4}$
Bus 2	20	80	0	1.75	$175 \cdot 10^{-4}$
Bus 5	15	50	0	1.00	$625 \cdot 10^{-4}$
Bus 8	10	35	0	3.25	$83 \cdot 10^{-4}$
Bus 11	10	30	0	3.00	$250 \cdot 10^{-4}$
Bus 13	12	40	0	3.00	$250 \cdot 10^{-4}$

Does have end to prove that the set of the three parameters of the colony of ants β , ρ and $q\theta$ is extensively independent of the problem of optimization to solve, we applied ACO-OPF on the network IEEE test 30 buses while using the 10 better combinations of the three parameters β , ρ and $q\theta$ and that give the best results for commercial traveler problem for the case of 30 cities [28]. The (Table 2) shows the values of actives powers, the losses of powers and the cost of fuel for the 10 ensemble wholes of parameters. We observe that all results are very near of the optimum. The average value of the cost for the 10 cases is the order of 804.087 \$/h. The value min of the cost is 803.123\$/h corresponds a ($\beta = 12$, $\rho = 0.5$ and $q\theta = 0.3$) with losses of powers 9.4616 MWS, while the bad value is 805.082 \$/h correspond a ($\beta = 10$, $\rho = 0.6$ and $q\theta = 0.3$) with losses of powers 9.1472 MWS.

Therefore we remark that even the most distant cost value is acceptable since it is on the one hand moves away of the value min with only 0.23% and on the other hand the value of the losses corresponds has this value that is 9.1472 MWS is better than the one corresponds at the value min with a report of 3.44%.

Table 2. Results of the ACO-OPF for the 10 ensemble wholes of parameters β , ρ and $q0$ for the IEEE 30-bus Electrical Network

Results	$\beta = 10$ $\rho = 0.6$ $q0 = 0.0$	$\beta = 11$ $\rho = 0.5$ $q0 = 0.1$	$\beta = 9.5$ $\rho = 0.8$ $q0 = 0.1$	$\beta = 10$ $\rho = 0.6$ $q0 = 0.3$	$\beta = 12$ $\rho = 0.5$ $q0 = 0.3$
$Pg1$ [MW]	174,8039	180,7298	175,9048	166,9419	177,8635
$Pg2$ [MW]	44,3193	49,9162	44,6092	55,4272	43,8366
$Pg5$ [MW]	23,5156	16,4104	19,7007	20,4983	20,893
$Pg8$ [MW]	23,6973	17,1032	21,1711	16,6558	23,1231
$Pg11$ [MW]	13,7473	15,6703	15,7906	15,7597	14,0255
$Pg13$ [MW]	12,5035	13,5907	15,6232	17,2643	13,1199
Power Loss [MW]	9,1869	10,0206	9,3996	9,1472	9,4616
Generation cost [\$/hr]	803,266	804,698	803,796	805,082	803,123
Results	$\beta = 9$ $\rho = 0.4$ $q0 = 0.4$	$\beta = 11$ $\rho = 0.8$ $q0 = 0.0$	$\beta = 10$ $\rho = 0.8$ $q0 = 0.6$	$\beta = 6$ $\rho = 0.3$ $q0 = 0.7$	$\beta = 11$ $\rho = 0.4$ $q0 = 0.4$
$Pg1$ [MW]	177,193	181,0254	178,0545	172,0554	180,7587
$Pg2$ [MW]	45,1405	43,6051	42,1303	51,1093	48,0675
$Pg5$ [MW]	24,9288	20,3537	19,0251	23,3981	19,6185
$Pg8$ [MW]	17,3428	15,9832	21,9837	17,3355	14,5895
$Pg11$ [MW]	11,0067	14,9995	17,8501	13,6159	17,9866
$Pg13$ [MW]	17,2079	17,1816	13,8232	15,154	12,2401
Power Loss [MW]	9,4197	9,7485	9,4669	9,2682	9,8609
Generation cost [\$/hr]	804,486	804,382	804,655	803,412	803,965

Results deliberate by ACO-OPF that corresponds at ensemble ($\beta = 12$, $\rho = 0.5$ and $q0 = 0.3$) are compare with those find by the QN method using the formula Update of BFGS and iterated with load flow of Newton Raphson (NR). The QN method uses a vector of penalty associates with the vector of controls Pgi . The values of the penalty coefficients are based on the formula of the B-coefficients losses. The use of the penalty functions that serves has keep the reactive powers of PV-bus in their admissible limits can produce problems of convergence that are practically has the distortion of the solution surface.

The constraints of security are also verified for the angles and the amplitudes of tensions, the levels of voltage (Per Unit) for the IEEE 30-bus Electrical Network are drawn in the Fig. 2. In ACO-OPF, we not make recourse for functions of penalty being given that only

the active powers of the generators are used in the selective function and the reactive powers are planned in the process of load flow. The essential of this idea is that the constraints are shared in two types: the active constraints that are verified by the procedure of ACO whereas the reactive constraints are update while using a procedure efficient of load flow by Newton-Raphson.

The results gotten including the generated cost and the losses of powers are compare with those acquired by the QN approved method and present on the Table 3.

Table 3. Comparison of the results gotten by ACO-OPF and QN-OPF on the IEEE 30-bus Electrical Network

Results	Min limit	Max limit	N-R	QN-OPF	ACO-OPF
$Pg1$ [MW]	50	200	99.211	170.237	177.8635
$Pg2$ [MW]	20	80	80.00	44.947	43.8366
$Pg5$ [MW]	15	50	50.00	28.903	20.8930
$Pg8$ [MW]	10	35	20.00	17.474	23.1231
$Pg11$ [MW]	10	30	20.00	12.174	14.0255
$Pg13$ [MW]	12	40	20.00	18.468	13.1199
Power Loss [MW]			5.812	8.805	9.4616
Generation cost [\$/hr]			901.918	807.782	803.123

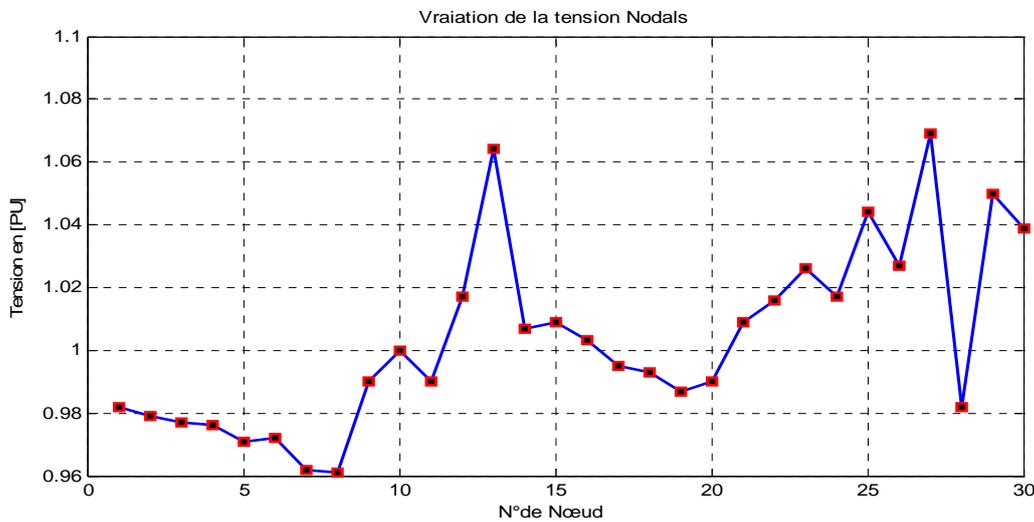


Figure 2. The levels of voltage (Per Unit) for the IEEE 30-bus Electrical Network

The ACO-OPF method is also compared with the evolutionary methods of the references [29, 30]. The first publication of Lai [29] is based on the AGs combined with the dynamic hierarchy of the coding of the system, and it to be capable to code a number important of variables of controls and with a reasonable character length. The second

publication of Janson Yuryevich and Kit Po Wong [30] is evolutionary programming with the inclusion of the information of gradient to accelerate research in local spaces. A comparison between the generate active powers calculated by the ACO and the evolutionary methods as well as the costs, the losses of active power and the time of convergence has been illustrated in the Table 4. It is important to note that the gotten results are similar those given by the evolutionary programming. Since the difference between the cost values resulting from the ACO-OPF only defers of the GA-OPF by a rate of 0.08% and of the EP-OPF by a rate of 0.07%. The value of the losses found by ACO-OPF that is of 9.4616 MWS is lower than the one found with GA-OPF by a rate of 1.85% and higher of the one of the EP-OPF by a rate of 0.98%. ACO-OPF can find better results if she optimizes the sizes of the battery system of capacitors and the numbers of holds loads transformers implemented in the IEEE network 30 buses as he has been made in the two methods of references [29, 30]. We add that the ACO-OPF is important to underline that the computer time for our method is better than the two other evolutionary methods.

Table 4. Comparison of the ACO-OPF with different evolutionary methods of optimization viewpoint cost, losses and times of convergence

Results	Min limit	Max limit	GA-OPF [29]	EP-OPF [30]	ACO-OPF
<i>Pg1</i> [MW]	50	200	178.0872	173.8262	177.8635
<i>Pg2</i> [MW]	20	80	48.722	49.998	43.8366
<i>Pg5</i> [MW]	15	50	21.454	21.386	20.8930
<i>Pg8</i> [MW]	10	35	20.954	22.63	23.1231
<i>Pg11</i> [MW]	10	30	11.768	12.928	14.0255
<i>Pg13</i> [MW]	12	40	12.052	12.00	13.1199
Generation cost [\$ /hr]			802.4484	802.5557	803.123
Power Loss [MW]			9.6372	9.3683	9.4616
Time [Sec]			315	51.4	20

Conclusions

Research in the area of metaheuristics has made possible the development of optimization methods that have the goal of providing high-quality solutions to complex systems. In this paper, an Ant Colony Optimization approach to the Optimal Power Flow problem is introduced and tested. This method would be very useful for power planner and/or



operator treat not only cost but also with environmental objective power system. As a study case, the IEEE 30 Bus system with six generating units has been selected. The simulation results show that for medium-scale system an ant colony optimization method can give a best result with reduced time. To save an important CPU time, the constraints are to be decomposing into active constraints and passives ones. The active constraints are the parameters which enter directly in the cost function and the passives constraints are affecting the cost function indirectly. In this approach, only the active constraints are taken to calculate the optimal solution set using ACO method and the passive constraints are taken in an efficient load flow by recalculating active power of the slack bus. The proposed method can be useful for large scale power system.

References

1. Dommel H.W., Tinney W.F., *Optimal Power Flow Solutions*, *IEEE Transactions on power apparatus and systems*, vol. PAS.87, No. 10, 1968, p. 1866-1876.
2. Bouktir T., Belkacemi M., Zehar K., *Optimal power flow using modified gradient method*, Proceedings ICEL'2000, U.S.T. Oran, Algeria, 2000, p. 436-442.
3. Fletcher R., *Practical Methods of Optimization*, John Willey & Sons, 1986.
4. Dorigo M., *Optimization, learning, and natural algorithms*, Ph.D. Dissertation (in Italian), Dipartimento di Elettronica, Politecnico di Milano, Italy, 1992.
5. Dorigo M., Di Caro G., *The ant colony optimization metaheuristic*, in Corne D., Dorigo M., Glover F., *New Ideas in Optimization*, McGraw-Hill, p. 11-32, 1997.
6. Dorigo M., Di Caro G., Gambardella L. M., *Ant algorithms for discrete optimization*, *Artificial Life*, Vol. 5, No. 2, p. 137-172, 1999.
7. Dorigo M., Maniezzo V., Colomi A., *Ant System, optimization by a colony of cooperating agents*, *IEEE Trans. System Man. and Cybernetics, Part B: Cybernetics*, Vol. 26, No. 1, p. 29-41, 1996.
8. Dorigo M., Gambardella L. M., *Ant colonies for the traveling salesman problem*, *BioSystems*, Vol. 43, p. 73-81, 1997.

9. Dorigo M., Gambardella L. M., *Ant colony System: a cooperative learning approach to the traveling salesman problem*, IEEE Transactions on Evolutionary Computation, Vol. 1, No. 1, p. 53-66, 1997.
10. Maniezzo V., Colomi A., *The ant System applied to the quadratic assignment problem*, IEEE Trans. Knowledge and Data Engineering, Vol. 11, No. 5, p. 769-778, 1999.
11. Stuetzle T., Dorigo M., *ACO algorithms for the quadratic assignment problem*, in Corne D., Dorigo M., Glover F., *New Ideas in Optimization*, McGraw-Hill, 1999.
12. Bullnheimer B., Häiti R. F., Strauss C., *Applying the ant System to the vehicle routing problem*, in Voss S., Martello S., Osman I. H., Roucairol C., *MetaHeuristics: Advances and Trend in Local Search Paradigms for Optimization*, Kluwer, p. 285-296, 1999.
13. Bullnheimer B., Häiti R. F., Strauss C., *An improved ant System algorithm for the vehicle routing problem*, Ann. Oper. Res., Vol. 89, p. 319-328, 1999.
14. Gambardella L. M., Taillard E., Agazzi G.: *MACS-VRPTW a multiple ant colony System for vehicle routing problems with time Windows*, in Corne D., Dorigo M., Glover F., *New Ideas in Optimization*, McGraw-Hill, p. 63-76, 1999.
15. Di Caro G., Dorigo M., *Ant colonies for adaptive routing in packet-switched communication networks*, Proc. 5th Int. Conf. Parallel Problem Solving From Nature, Amsterdam, The Netherlands, p. 673-682, 1998.
16. Costa D., Hertz A., *Ants can color graphs*, J. Oper. Res. Soc., Vol. 48, 1997, p. 295-305.
17. Schoofs L., Naudts B., *Ant colonies are good at solving constraint satisfaction problems*, Proc. 2000 Congress on Evolutionary Computation, San Diego, CA, p. 1190-1195, 2000.
18. Wagner I. A., Bruckstein A. M., *Hamiltonian(t)-an ant inspired heuristic for recognizing Hamiltonian graphs*, Proc. 1999 Congress on Evolutionary Computation, Washington, D.C., p. 1465-1469, 1999.
19. Bauer A., Bullnheimer B., Hartl R. F., Strauss C., *Minimizing total tardiness on a single machine using ant colony optimization*, Central Eur. J. Oper. Res., Vol. 8, No. 2, p. 125-141, 2000.
20. Colomi A., Dorigo M., Maniezzo V., Trubian M., *Ant system for job-shop scheduling*, Belgian J. Oper. Res., Statist. Comp. Sci. (JORBEL), Vol. 34, No. 1, p. 39-53, 1994.



21. Den Besteb M., Stützle T., Dorigo M., *Ant colony optimization for the total weighted tardiness problem*, Proc. 6th Int. Conf. Parallel Problem Solving from Nature, Berlin, p. 611-620, 2000.
22. Merkle D., Middendorf M., *An ant algorithm with a new pheromone evaluation rule for total tardiness problems*, Proceedings of the EvoWorkshops 2000, Berlin, Germany: Springer-Verlag, Vol. 1803 then Lecture Notes in Computer Science, 2000, p. 287-296.
23. Wood A. J., Wollenberg B.F., *Power Generation, Operation and Control*, 2nd Edition, John Wiley, 1996.
24. Del Toro V., *Electric Power Systems*, Vol. 2, Prentice Hall, Englewood Cliffs, New Jersey, USA, 1992.
25. Stagg G. W., El Abiad A. H., *Computer methods in power systems analysis*, McGraw Hill International Book Company, 1968.
26. Kumar S., Billinton R., *Low bus voltage and ill-conditioned network situation in a composite system adequacy evaluation*, IEEE Transactions on Power Systems, Vol. PWRS-2, No. 3, 1987.
27. Johnson D.S., McGeoch L.A., *The traveling salesman problem: a case study in local optimization*, in E. H. L. Aarts, J. K. Lenstra: Local Search in Combinatorial Optimization, John Wiley and Sons, p. 215-310, 1997.
28. Gaertner D., *Natural Algorithms for Optimisation Problems*, 'Final Year Project Report' June 20, 2004,
29. Lai L. L., Ma J. T., Yokoma R., Zhao M., *Improved genetic algorithms for optimal power flow under both normal and contingent operation states*, Electrical Power & Energy, System, Vol. 19, No. 5, p. 287-292, 1997.
30. Yuryevich J., Wong K. P., *Evolutionary Programming Based Optimal Power Flow Algorithm*, IEEE Transaction on power Systems, Vol. 14, No. 4, November 1999.