ANT COLONY OPTIMIZATION FOR ACTIVE/REACTIVE OPERATIONAL PLANNING

Kwang Y. Lee* and John G. Vlachogiannis**

** Department of Electrical Engineering*
The Pennsylvania State University, PA 16803, USA
(email: kwanglee @ psu.edu)
*** Industrial & Energy Informatics Laboratory*
R.S. Lianokladiou, 35100, Lamia, Greece,
(email: vlachogiannis @ usa.com)

Abstract: This paper proposes the application of Ant Colony Optimization (ACO) for active/reactive operational planning of power systems. The ACO is a newly developed method belonging to the class of evolutionary computation methods inspired from real ants life. Specifically, ACO algorithm aims to determine the optimal settings of control variables, such as generator outputs, generator voltages, transformer taps and shunt VAR compensation devices, considered as nodes of an Ant-System (AS) graph. Results are compared to those given by Simulated Annealing for the IEEE 30-bus test system, exhibiting superior performance.

Keywords: Power systems, Operational Planning, Assisted control, Generation, Supply Voltages, Flow, Artificial Intelligence

1. INTRODUCTION

Modern power systems have many operations such as the dispatch of active power and others known as ancillary services. Active/reactive operational planning belongs to this category of services. It allocates Volt control and reactive support in accordance with open market mechanisms (Papadogiannis, *et al.,* 2003). Many research works (Bhattacharya and Zhong, 2001; Dandachi, *et al.,* 1996; Gross, *et al.,* 2002; Lee, *et al.,* 1984, 1985, 1988; Papadogiannis, *et al.,* 2003; Silva, *et al.,* 2001) reveal the coupling between active and reactive power support, some others (Dona and Peredes, 2001; El-Keib and Ma, 1997) try to evaluate reactive power short-term marginal prices and Hao and Papalexopoulos (1997) propose the development of local reactive power markets. Zammit et al. (2000) design ancillary service markets considering firstly security and secondly economic optimization in combination with spot market for electricity. Recently, the discrete nature of the problem leading to the use of meta-heuristic techniques such as Simulated Annealing (SA) and Genetic Algorithms (GA) (Lee, *et al.,* 1995; Chen and Liu, 1995; Chen, 1996; Hsiao, *et al.,* 1994; Huang, *et al.,* 1998; Papadogiannis, *et al.,* 2003; Wong and Suzannah, 1996; Yang, *et al.,* 1996).

In this paper, the active/reactive operational planning is solved by means of the heuristic Ant Colony Optimization (ACO) method. Dorigo (1992) has proposed the first ACO in his Ph.D. thesis. The ACO method belongs to biologically inspired heuristics (meta-heuristics) methods (Dorigo, *et al.,* 1996; Dorigo and Cambardella, 1997; Dorigo and Di Caro, 1999). Real ants are capable of finding the shortest path from food source to their nest, without using visual cues, but by exploiting pheromone information. While walking, real ants deposit pheromone trails on the ground and follow pheromone previously deposited by other ants. This behavior has inspired the ACO algorithm in which a set of artificial ants cooperate in solving a problem by exchanging information via pheromone deposited on a graph. Specifically, in this paper, ACO algorithm aims to determine the optimal settings of voltage control variables, such as generator outputs, voltages, transformer taps and shunt VAR compensation devices (Chiou, *et al.,* 2004), considered as nodes of Ant-System (AS) graph (Dorigo, 1992; Dorigo, *et al.,* 1996; Dorigo and Cambardella, 1997; Dorigo and Di Caro, 1999). Results are compared to those given by meta-heuristic technique of Simulated Annealing (Papadogiannis, *et al.,* 2003) for the network of IEEE 30-bus test system, exhibiting superior performance.

2. MATHEMATICAL FORMULATION

The ancillary services studied in this paper include firstly economic resource allocation considering typical bid structure and secondly security management. Specifically, the minimization of the offered bid cost, the constraints of basic components and the steady state transmission line loadings are examined. Therefore, the problem of active/reactive operational planning is formulated as an optimization problem considering as objective function, the cost minimization expressed by:

$$C_T^t = Min \sum_{i \in Ng} C_i^t (P_{gi}^t) \qquad (1)$$

where

C_T^t is the total cost

C_i^t is the active power cost of unit-*i* at time-*t*

P_{gi}^t is active power generation of unit-*i* at time-*t*

Ng is the total number of units

under the following mild constraints:

a) *Generation constraints:* Generator voltages, active and reactive powers restricted by lower and upper limits.
b) *Transformer constraints:* Transformer taps bounded by lower and upper limits.
c) *Shunt VAR constraints:* Shunt VAR compensation restricted by its capacity.
d) *Security constraints:* Steady State transmission line loadings.

The above inequalities are incorporated in the objective function (1) as quadratic highly penalty terms (Dorigo, *et al.,* 1996).

3. ACO FOR ACTIVE/REACTIVE OPERATION PLANNING

The settings of control variables (generator voltages, active powers tap-settings, VAr compensation blocks, etc.) are combined in order to achieve the power system constraints. In our approach, the graph that describes the settings of control variables of the active/reactive operational planning is mapped on the AS-graph, which is the space that the artificial ants will walk. Fig. 1 shows the AS-graph (searching space) for the active/reactive operational planning. All possible candidate discrete settings for a control variable are represented by the states *r* of the AS-graph (*r* = 1, …, *m*). The control variables are represented by the stages *i* (*i* = 1, ..., *n*), where *n* is the number of the control variables. Each ant will start its tour at the home colony and stop at the destination.

The ACO algorithm for active/reactive operation planning proceeds as follows (Table 1):
An operating point at time-t comprising a load and generation pattern (operating point of the whole planning period of the system) is randomly created. For this operating point, first of all AS graph is created and all paths receive an amount of pheromone that corresponds to an estimation of the best solution so that ants test all paths in the initial iterations. Therefore, ACO-algorithm achieves the best exploration of AS-graph in the earlier iterations of convergence and better exploitation at the latest. If the ant *k* is at point *r,* has the next point been visited? The ant *k* maintains a tabu list N_r^k in memory that defines the set of points still to be visited when it is at point *r*. Then, ant *k* chooses the next states to go to in accordance with the transition probability calculated by (2):

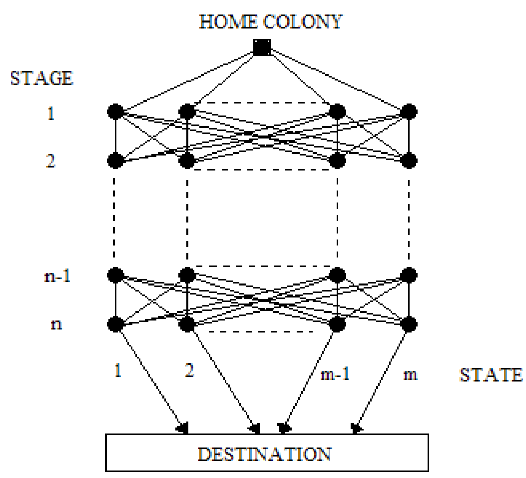

Fig.1. Search space for the active/reactive operation planning.

Table 1: ACO algorithm for active/reactive operational planning

1. Create the AS-graph (search space) that represents the discrete settings (states) of the control variables (stages).
2. Insert the pheromone matrix $\gamma(m,n)$ according to nodes of AS-graph, where n is the number of stages and m the number of states.
3. Initialize the pheromone matrix $\gamma(m,n) = \gamma_0(m,n) = \tau_{\max}$ (in (10), in this case f_{gbest} is an initial estimation of the best solution).
4. Do for an operating point.
4.1 Repeat until the system convergence or iteration is less than a given maximum number.
4.1.1 Place randomly M ants on the states of the 1st stage (i = 1).
4.1.2 For k=1 to M
4.1.2.1 For i = 2 to n
4.1.2.1.1 When the ant-k has selected the r-state of the (i-1)-stage, it currently chooses the s-state of the (i)-stage in which will move according to transition rule (2)
4.1.2.1.2 Move the ant-k to s-state of i–stage.
4.1.2.1.3 Record s to J^k, and set r =s
4.1.3 Run power flow
4.1.4 Calculate the objective function (5) for each ant
4.1.5 Update the pheromone of (r,s)-trails for each ant, using the local pheromone update formulae (3), (4)
4.1.6 Update the pheromone of (r,s)-trails belonging to best ant tour (f_{best}), using the pheromone update formula (8)
4.1.7 In order to avoid the ants stagnations, enforce the limits (9)-(11)

$$p(r,s) = \frac{\gamma(r,s)}{\sum_{l}\gamma(r,\ell)} \qquad s,\ \ell \in N_r^k \tag{2}$$

where matrix $\gamma(r,s)$ represents the amount of the pheromone trail, pheromone intensity, between points r and s.

When the ant k moves from one stage to the next, the state of each stage will be recorded in a location list J^k. After the tour of ant k is completed, its location list is used to compute its current solution.
Then the pheromone trails composed by nodes of location list J^k are updated in accordance with (3) (local update):

$$\gamma(r,s) = \alpha \cdot \gamma(r,s) + \Delta\gamma^k(r,s) \tag{3}$$

For the purpose of this research, the pheromone update $\Delta\gamma^k(r,s)$ is chosen as:

$$\Delta\gamma^k(r,s) = \frac{1}{Q \cdot f} \tag{4}$$

where f is the objective function, and Q is a large positive constant.

Application of the ACO algorithm to the active/reactive operational planning is linked to the choice of an objective function f, which incorporates all linear/nonlinear constraints related with voltages, flows, real outputs of generators, reactive sources and transformer taps. For comparison purpose the evaluation function f is chosen this given in (Papadogiannis, *et al.,* 2003):

$$\begin{aligned} f = C_T^t + \sum_{i=1}^{N}\left(V_i^t - V_i^{\max}\right)\cdot p(V) + \\ \sum_{i=1}^{N}\left(V_i^{\min} - V_i^t\right)\cdot p(V) + \sum_{j=1}^{Nb}\left(\frac{I_j^t}{I_j^{\max}} - 1\right)\cdot p(I) \end{aligned} \tag{5}$$

where N is the total number of buses, Nb is the set of network branches, $V_i^{\min}, V_i^{\max}$ are the limits of voltage at bus-i, and $I_j^{\max}$ is the limit for the transmission line-j.

The penalty factors $p(V)$ and $p(I)$ enforces the voltage and thermal limits:

$$p(V) = \begin{cases} 40 & \text{if } V_i^t > V_i^{\max} \ or \ V_i^t < V_i^{\min} \\ 0 & \text{else} \end{cases} \tag{6}$$

$$p(I) = \begin{cases} 300 & \text{if } I_j^t > I_j^{\max} \\ 0 & \text{else} \end{cases} \tag{7}$$

In order to exploit the iteration in finding the best solution, the next two steps are considered:

a) When all ants complete their tours, the pheromone trails (r,s) of the best ant tour (ant with minimum objective function (5)) is updated (global update) as:

$$\gamma(r,s) = \alpha \cdot \gamma(r,s) + \frac{R}{f_{best}} \qquad r,\ s\ \in J_{best}^k \tag{8}$$

where R is a large positive constant.

Both Q in (4) and R are arbitrarily large numbers. Empirical tests have shown that the ACO-algorithm converges faster when Q is almost equal to R.

b) To avoid search stagnation (the situation where all ants follow the same path, that is, they construct the same solution (Dorigo and Cambardella, 1997)), the allower range of the pheromone trail strengths is limited to:

$$\gamma\ (r,s) = \begin{cases} \tau_{\min} & \text{if } \gamma\ (r,s) \le \tau_{\min} \\ \tau_{\max} & \text{if } \gamma\ (r,s) \ge \tau_{\max} \end{cases} \tag{9}$$

For our study the limits are chosen as:

$$\tau_{\max} = \frac{1}{\alpha \cdot f_{gbest}} \tag{10}$$

where f_{gbest} is the global best solution (best over the whole past iterations), and

$$\tau_{\min} = \frac{\tau_{\max}}{M^2} \tag{11}$$

where M is the number of ants. The ACO procedure can be repeated for a large number of operating states covering the whole planning period.

4. CASE STUDY

The proposed algorithm is applied on the IEEE 30-bus test system. The topology and the complete data of this network can be found in: *http://www.ee.washington.edu/research/pstca/pf30/pg_tca30bus.htm*.

The network consists of 4 generators, 41 lines, 4 transformers and 2 capacitor banks. In the transformer tests, 7 tap positions in each transformer were considered. Each position corresponds to 0.02 increments within the interval [0.94, 1.06]. The available reactive powers of capacitor banks are [0, 7.5, 15, 22.5, 30] MVAr and they are connected to buses 10 and 24. Generator voltages are discretized in 150 steps (step: 0.0006 pu) within the range of [0.96, 1.05]. Loads were set at the values referred in *http://www.ee.washington.edu/research/pstca/pf30/pg_tca30bus.htm*, multiplied by a factor of 0.6 (nominal load). The increment/decrement accuracy for the generator outputs was set to 1MW/0.01 pu. The bid curves of four generators and the minimum and maximum submitted capacities are given by (Papadogiannis, *et al.,* 2003):

$$\text{bid}(P_1) = \begin{Bmatrix} 10€/\text{MWh}\ 50\text{MW} \le P_1 < 80\text{MW} \\ 20€/\text{MWh}\ 80\text{MW} \le P_1 < 110\text{MW} \\ 30€/\text{MWh}\ 110\text{MW} \le P_1 < 140\text{MW} \\ 40€/\text{MWh}\ 140\text{MW} \le P_1 < 170\text{MW} \\ 50€/\text{MWh}\ 170\text{MW} \le P_1 \le 200\text{MW} \end{Bmatrix} \tag{12}$$

$$\text{bid}(P_2) = \begin{Bmatrix} 10€/\text{MWh}\ 20\text{MW} \le P_2 < 36\text{MW} \\ 20€/\text{MWh}\ 36\text{MW} \le P_2 < 52\text{MW} \\ 30€/\text{MWh}\ 52\text{MW} \le P_2 < 68\text{MW} \\ 40€/\text{MWh}\ 68\text{MW} \le P_2 < 84\text{MW} \\ 50€/\text{MWh}\ 84\text{MW} \le P_2 < 100\text{MW} \end{Bmatrix} \tag{13}$$

$$\text{bid}(P_3) = \begin{Bmatrix} 10€/\text{MWh}\ 10\text{MW} \le P_3 < 18\text{MW} \\ 20€/\text{MWh}\ 18\text{MW} \le P_3 < 26\text{MW} \\ 30€/\text{MWh}\ 26\text{MW} \le P_3 < 34\text{MW} \\ 40€/\text{MWh}\ 34\text{MW} \le P_3 < 42\text{MW} \\ 50€/\text{MWh}\ 42\text{MW} \le P_3 \le 50\text{MW} \end{Bmatrix} \tag{14}$$

$$\text{bid}(P_4) = \begin{Bmatrix} 10€/\text{MWh}\ 3\text{MW} \le P_4 < 5.4\text{MW} \\ 20€/\text{MWh}\ 5.4\text{MW} \le P_4 < 7.8\text{MW} \\ 30€/\text{MWh}\ 7.8\text{MW} \le P_4 < 10.2\text{MW} \\ 40€/\text{MWh}\ 10.2\text{MW} \le P_4 < 12.6\text{MW} \\ 50€/\text{MWh}\ 12.6\text{MW} \le P_4 \le 15\text{MW} \end{Bmatrix} \tag{15}$$

In our study, the following ACO parameters are chosen: $M = 300$, $n = 14$, $m = 150$, $Q = R = 5{,}000{,}000$ and the initial best solution is estimated at 0.1. The parameter α in (3) from our experience shows that any value in the range [0.88, 0.999] works well. In this paper it is chosen as $\alpha = 0.99$. In this study, the search will terminate if one of the following criteria is satisfied: a) the number of iterations since the last change of the best solution is greater than 1000 iterations, or b) the number of iterations reaches to 3000 iterations.

The ACO algorithm converges in 2010 iterations (Fig. 2) and the final value of function (5) was 3050 €. The final value given by Simulated Annealing (Papadogiannis, *et al.,* 2003) method is 3141 €. An improvement of 91€ is obtained compared to the evaluation given by SA (Papadogiannis, *et al.,* 2003). The final settings of control variables for ACO and SA are given in Table 2. It is shown that the generator outputs given by ACO algorithm are slightly different from those given by SA (Papadogiannis, *et al.,* 2003).

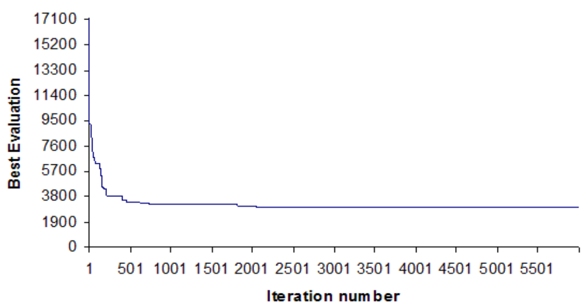

Fig. 2. Performance of ACO algorithm in the nominal load.

Table 2 ACO's settings of control variables for IEEE 30-bus test system

Control Variables	ACO	SA
Output of gen. 1 (MW)	109	108
Output of gen. 2 (MW)	35	35
Output of gen. 3 (MW)	25	25
Output of gen. 4 (MW)	5	6
Voltage of gen. 1 (pu)	1.037	Fixed at 1.0
Voltage of gen. 2 (pu)	1.022	Fixed at 1.02
Voltage of gen. 3 (pu)	1.012	Fixed at 1.01
Voltage of gen. 4 (pu)	1.041	Fixed at 1.02
Tap setting 1	1.0	1.02
Tap setting 2	0.94	0.98
Tap setting 3	0.94	1.04
Tap setting 4	1.02	0.98
Capacitor bank 1 (MVAr)	0	0
Capacitor bank 2 (MVAr)	15	7.5

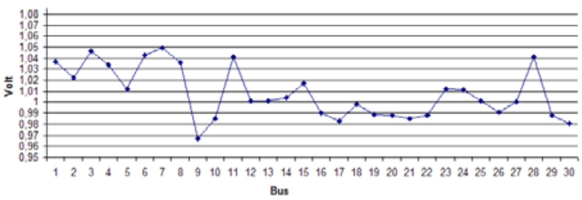

Fig. 3. Bus voltages.

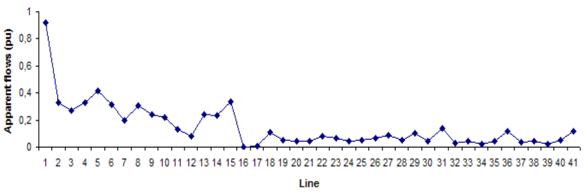

Fig. 4. Apparent flows (pu).

The bus voltages and apparent flows in pu are given in Figs. 3 and 4, respectively. The bus voltages are within the acceptable voltage range of [0.96, 1.05] as shown in Fig 3. According to Fig. 4 all branch apparent flows are much lower than the acceptable ranges of 202MW/2.02 pu (for 132 KV lines between buses: 1-2, 1-3, 2-4, 2-5, 2-6, 3-4, 4-6, 6-28, 5-7, 6-8, 6-7, 8-28) and 30MW/0.3 pu (for 33 KV lines).

5. CONCLUSIONS

In this paper we present a coupled approach of active/reactive operational planning as an optimization problem in market environment. An ACO algorithm was implemented in order to solve this problem. Specifically, ACO algorithm determined the optimal settings of control variables, such as generator real outputs and voltages, transformer taps and shunt VAR compensation devices, which were considered as nodes of the implemented AS-graph. Results are compared to those given by Simulated Annealing for IEEE 30-bus test system, exhibiting superior performance in the cost of power system satisfying all mild constraints.

REFERENCES

Bhattacharya, K. and J. Zhong (2001). Reactive power as an ancillary service. *IEEE Trans. on Power Syst.,* 16 (2), pp. 294-300.

Chen, Y.-L and C.-C. Liu (1995). Optimal multi-objective VAR planning using an interactive satisfying method. *IEEE Trans. on Power Syst.,* 10 (2), pp. 664-670.

Chen, Y.-L. (1996). Weak bus-oriented optimal multi-objective VAR planning. *IEEE Trans. on Power Syst.,* 11 (4), pp. 1885-1890.

Chiou, J.-P., C.-F. Chang and C.-T. Su (2004). Ant direction hybrid differential evolution for solving large capacitor placement problems. *IEEE Trans. on Power Syst.,* 19 (4), pp. 1794-1800.

Dandachi, N.H., M.J. Rawlins, O. Alsac, M. Prais and B. Stott (1996). OPF for reactive pricing studies on the NGC system. *IEEE Trans. on Power Syst.,* 11 (1), pp. 226-232.

Dona, V.M. and A.N. Peredes (2001). Reactive power pricing in competitive electric markets using the transmission losses function. *Proc. of IEEE 2001* Power Tech. Conf., Porto, Portugal, Sept. 2001.

Dorigo, M. (1992). *Optimization, learning and natural algorithms.* PhD Thesis, Politecnico de Milano, Italy, 1992.

Dorigo, M., V. Maniezzo and A. Colorni (1996). Ant system: Optimization by a colony of cooperating agents. *IEEE Trans. Syst., Man, Cybern. B,* 26 (1), pp. 29-41.

Dorigo M. and L. M. Cambardella (1997). Ant colony system: A cooperative learning approach to traveling salesman problem. *IEEE Trans. Evol., Comput.,* 1 (1), pp. 53-66.

Dorigo M. and G. Di Caro (1999). Ant colony optimization: A new meta-heuristics. *Proc. Congr. Evol. Computation,* 2, pp. 1470-1477.

El-Keib, A.A. and X. Ma (1997). Calculating short-run marginal costs of active and reactive power production. *IEEE Trans. on Power Syst.,* 12 (2), pp. 559-565.

Gross, G., S. Tao, E. Bompard and G. Chicco (2002). Unbundled reactive support service: Key characteristics and dominant cost component. *IEEE Trans. on Power Syst.,* 17(2), pp. 283-289.

Hao, S. and A. Papalexopoulos (1997). Reactive power pricing and management. *IEEE Trans. on Power Syst.,* 12 (1), pp. 95-104.

Hsiao, Y.-T., H.-D. Chiang, C.-C. Liu and Y.-L. Chen (1994). A computer package for optimal multi-objective VAR planning in large scale power systems. *IEEE Trans. on Power Syst.,* 9 (2), pp. 668-676.

Huang, K.-Y., T.-T. Yang and C.-L. Huang (1998). A new thermal unit commitment approach using constraint logic programming. *IEEE Trans. on Power Syst.,* 13 (3), pp. 936-945.

Lee, K. Y., Y. M. Park and J. L. Ortiz (1984). Fuel cost minimization for both real and reactive power dispatches. *IEE Proceedings (London) C,* l3l, pp. 85-93.

Lee, K. Y., Y. M. Park and J. L. Ortiz (1985). A united approach to optimal real and reactive power dispatch. *IEEE Trans. on Power Appar. and Syst*, l04 (5), pp. ll47-ll53.

Lee, K. Y., J. L. Ortiz, M. A. Mohtadi and Y. M. Park (1988). Optimal operation of large-scale power systems. *IEEE Trans. on Power Syst.* 3 (2), pp. 4l3-420.

Lee, K. Y., X. Bai, and Y. M. Park (1995). Optimization method for reactive power planning using a genetic algorithm. *IEEE Trans. on Power Syst.*, 10 (4), pp. 1843-1850.

Papadogiannis, K.A., N.D. Hatziargyriou and J.T. Saraiva (2003). Short term active/reactive operation planning in market environment using simulated annealing. *Proc. ISAP03,* Aug. 31-Sept. 3, 2003, Lemnos, Greece.

Silva, E.L., J. Hedgecock, J.C. Mello and J.C. Ferreira (2001). Practical cost based approach for the voltage ancillary service. *IEEE Trans. on Power Syst.,* 16 (4), pp. 806-812.

The IEEE 30-bus test system. Available online in: *http://www.ee.washington.edu/research/pstca/pf30 /pg_tca30bus.htm*

Wong, K.P. and Y.W. Suzannah (1996). Combined Genetic Algorithm / Simulated Annealing /Fuzzy Set approach. *IEEE Trans. on Power Syst.,* 11 (1), pp. 128-136.

Yang, Y.-T., P.-C. Yang and C.-L Huang (1996). Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions. *IEEE Trans. on Power Syst.,* 11(1), pp. 112-118.

Zammit, M.A.B., D.J. Hill and R.J. Kaye, (2000). Designing ancillary services markets for power system security. *IEEE Trans on Power Syst.,* 15 (2), pp. 675-680.