JCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-1, Jan 2019 E-ISSN: 2347-2693

Real Power Loss Reduction by Ant Colony Search Algorithm

Kanagasabai Lenin

Department of EEE Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh -520007, India

Corresponding Authors: gklenin@gmail.com

Available online at: www.ijcseonline.org

Accepted: 27/Jan2019, Published: 31/Jan/2019

Abstract- The paper presents Ant colony search Algorithm (ACSA) for solving optimal reactive power problem. ACSA algorithms are developed based on the observation of foraging behavior of real ants. Although they are almost blind animals with very simple individual capacities, they can find the shortest route between their nest(s) and a source of food without using visual cues. They are also capable of adapting to changes in the environment; finding a new shortest path once the old one is no longer feasible due to a new obstacle. The studies by ethnologists reveal that such capabilities are essentially due to what is called pheromone trails, which ants use to communicate information among individuals regarding path and to decide where to go. During their trips a chemical trail (pheromone) is left on the ground. The pheromone guides other ants towards the target point. Furthermore, the pheromone evaporates over time. If many ants choose a certain path and lay down pheromones, the quantity of the trail increases and thus this trail attracts more and more ants. Each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one. Proposed algorithm has been tested in standard IEEE 300 bus system and simulation results reveals about the better performance of the proposed algorithm in reducing the real power loss.

Keywords: Reactive power, Transmission loss, Ant colony search algorithm

I. INTRODUCTION

The reactive power optimization problem has a significant influence on secure and economic operation of power systems. A variety ofnumerical techniqueslike the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods has the complexity in controlling inequality constraints. If linear programming is applied, then the input- output function has to be articulated as a set of linear functions which predominantly lead to loss of accuracy. Thedifficulty of voltage stability and fall down, play a major role in power system planning and operation [8]. Global optimization has received wide-ranging research responsiveness, and enormousnumber of methods has been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9,10].Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable incessant space functions. In [11], Genetic algorithm has been used to solve optimal reactive power flow problem. In [12], Hybrid differential evolution algorithm is proposed to perk up the voltage stability index. In [13],Biogeography Based algorithm is planned to solve the reactive power dispatch problem. In [14], afuzzy based method is used to solve the optimal reactive power scheduling method. In [15],an improved evolutionary programming is used to solvethe optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinearinterior point method. In [17], apattern algorithm is used to solve ac-dc optimal reactive powerflow model with the generator capability limits. In [18], proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based proposed approach used to solve the optimal reactive power dispatch problem. In [20], presents aprobabilistic algorithm for optimal reactive power requirementin hybrid electricity markets with uncertain loads. The paper presents Ant colony search Algorithm (ACSA) for solving optimal reactive power problem. ACSA are developed based on the observation of foraging behavior of real ants. Although they are almost blind animals with very simple individual capacities, they can find the shortest route between their nest(s) and a source of food without using visual cues. They are also capable of adapting to changes in the environment; finding a new shortest path once the old one is no longer feasible due to a new obstacle. The studies by ethnologists reveal that such capabilities are essentially due to what is called pheromone trails, which ants use to communicate information among individuals regarding path and to decide where to go. During their trips a chemical trail (pheromone) is left on the ground. The pheromone guides other ants towards the target point. Furthermore, the pheromone evaporates over time. Proposed algorithm has been tested in standard IEEE 300 bus system and simulation results reveals about the better performance of the proposed algorithm in reducing the real power loss.

II. PROBLEM FORMULATION

The objective of the reactive power dispatch problem is to minimize the active power loss and can be defined in equations as follows:

$$F = PL = \sum_{k\in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \quad (1)$$

Where gk : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems.

Voltage profile improvement

To minimize the voltage deviation in PQ buses, the objective function can be written as:

$$F = PL + \omega_v \times VD \quad (2)$$

Whereω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

$$P_G = P_D + P_L \quad (4)$$

Where the total power generation PG has to cover the total power demand PD and the power losses PL.

Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators are written as follows :

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \quad (6)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \quad (7)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \quad (8)$$

Upper and lower bounds on the compensators

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \quad (9)$$

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

III. ANT COLONY SEARCH ALGORITHM

Ant colony search algorithm (ACSA) is a new cooperative agent’s approach which is inspired by the observation of the behavior of real ant colonies on the topic of ant trial formation and foraging methods. For the last few years, the algorithms inspired by the observation of natural phenomena to help solving complex combinatorial problems have been increasing interest. In analyzing the behaviors of real ants, it was found that the ants are capable of finding shortest path from food sources to the nest without using visual cues [21].

In ACSA the state transition rule is as follows: an ant positioned on node *r* chooses the city *s* to move to by applying the rule given by Equation as follows. $S =$

$$\begin{cases} \text{Arg} \max_{w\in J_{k(r)}} \{ [\tau(r,u)] . [\eta(r,u)]^{\beta} \}, \text{ if } q \le q_0, \text{(exploitation)} \end{cases} \quad (10)$$

S, otherwise (biased exploration)

Where

q is a random number uniformly distributed in [0 …1]

q_0 is a parameter ($0 \le q_0 \le 1$)

S is a random variable selected according to the probability distribution

The state transition rule used by ant system, called a random-proportional rule, which gives the probability with which ant *k* in city *r* chooses to move to the city *s*.

$$P_k(r,s) = \begin{cases} \dfrac{[\tau(r,s)] \bullet [\eta(r,s)]^{\beta}}{\sum_{\mu\in J_k(r)} [\tau(r,u)] \bullet [\eta(r,u)]^{\beta}}, \textit{if } s \in J_k(r) \\ 0, \textit{otherwise} \end{cases}$$

(11)

where:

τ is the pheromone

$J_k(r)$ is the set of cities that remain to be visited by ant *k* positioned on city *r* (to make the solution feasible)

β is a parameter, which determines the relative importance of pheromone versus distance (β > 0)

$\eta = I/\delta$ is the inverse of the distance δ (r,s). Global updating is performed after all ants have completed their tours. The pheromone level is updated by applying the global updating rule as follows

$\tau(r,s) \leftarrow (1-a).\tau(r,s) + \alpha.\Delta\tau(r,s)$ (12)

$$\Delta\tau(r,s) = \begin{cases} (L_{gb})^{-1} \text{ I } f \ (r,s) \in \text{global-best} - 4 \\ 0, \text{ otherwise} \end{cases}$$

α is the pheromone decay parameter ($0<\alpha$ 1) L_{gb} is the length of the globally best tour from the beginning of the trial.

Changing the pheromone level by applying the local updating rule

$\tau(r,s) \leftarrow (1-p)\,\tau(r,s) + p.\Delta\tau(r,s)$ … (13)

Where ;

p is a heuristically defined coefficient ($O<p<1$)

$\Delta\tau(r,s) = \tau_0$,

τ_0 is the initial pheromone level

Each trail is a discrete random variable in the pheromone matrix. The entropy of a random variable is defined as

$$\mathbf{E(X)} = -\sum_{i=1}^{r} P_i \log P_i \qquad \textbf{(14)}$$

where p_i represents the probability of occurrence of each trails in the pheromone matrix. For a symmetric n cities, there are $n(n-1)/2$ distinct pheromone trails and $r= n(n-1)/2$. It is easy to see that when the probability of each trail is the same, E will be the maximum (denoted as E_{max}) and is given by

$$E_{max} = -\sum_{i=1}^{r} P_i \log P_i = -\sum_{i=1}^{r} \frac{1}{r} \log\frac{1}{r} = \log r \qquad (15)$$

β is update according to the rule given by β =

$$\begin{cases} 5 & \text{threshold } X < E` \leq 1 \\ 4 & \text{threshold } Y < E` \leq X \\ 3 & \text{threshold } Z < E` \leq Y \\ 2 & \text{threshold } 0 < E` \leq Z \end{cases}$$

$$E` = 1 - \frac{E_{max} - E_{current}}{E_{max}} \qquad (16)$$

Where E' is the entropy value for the current pheromone matrix and X, Y and Z are thresholds according to the city size. In study, threshold X is set within 0.8~0.9and threshold B is within0.75~0.55, and threshold Z is decided heuristically based on the value of Y.

Set parameters, initialize pheromone trails
Calculate the maximum entropy
Loop /* at this level each loop is called iteration*/
Each ant is positioned on a starting node according to Distribution strategy (each node has at least one ant)
For k=1 to m do /*at this level each loop is called a step */
At the first step moves each ant at different route
Repeat
Compute candidate list
Select node j to be visited next (the next city in the Candidate list) according to solution construction
A local updating rule is applied
Until ant k has completed a tour
End for
Local search (2-opt, 2.5 opt) apply to improve tour
A global updating rule is applied
Compute entropy value of current pheromone trails
Update the heuristic parameter
Until end_condition
end

IV. SIMULATION STUDY

IEEE 300 bus system [22] is used as test system to validate the performance of the proposed algorithm. Table 1 shows the comparison of real power loss obtained after optimization.

TABLE 1 COMPARISON OF REAL POWER LOSS

Parameter	Method EGA [24]	Method EEA [24]	Method CSA [23]	ACSA
PLOSS (MW)	646.2998	650.6027	635.8942	624.9896

V. CONCLUSION

In this work Ant colony search Algorithm (ACSA) successfully solved the optimal reactive power problem. Foraging behavior of real ants has been modelled to solve the problem. Each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one. Proposed algorithm has been tested in standard IEEE 300 bus system and simulation results reveal about the better performance of the proposed algorithm in reducing the real power loss.

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