# Transmission System Expansion Planning by Ant Colony Optimization: A case of China Southwest System

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***Abstract***

This paper proposes an application of ant colony optimization (ACO) to solve transmission system expansion planning (TSEP) problem based on DC power flow model. The main objective is to minimize the investment cost of transmission lines that should be added to an existing network in order to supply the forecasted load as economically as possible subject to many system constraints i.e. the power balance, the generation requirements, line connections and thermal limits. The TSEP problem was tested using the 18-bus of China Southwest system. The results obtained by ACO are compared to Genetic Algorithm (GA) in term of solution quality and computational efficiency. The experimental results show that the ACO method outperforms GA methods in terms of high quality solution, stable convergence characteristic and good computation efficiency.

***Keywords:*** Ant Colony Optimization, Genetic Algorithm and Transmission System Expansion Planning Problem

## 1. Introduction

Transmission system expansion planning (TSEP) is an important issue of electrical power system planning. The principle of TSEP is to establish an optimal configuration to be consistent with electricity demand and a generation planning scheme, meeting the requirement of delivering electricity sufficiently, safely and economically over the planning period. For that reason, TSEP addresses an optimization problem in the power system. The model of TSEP can be categorized as static and dynamic according to the treatment of the study period. Static planning involves a single horizontal planning and answering the questions of what and where type of new equipment should be installed in an optimal way that minimizes the installation and operational costs. Others, dynamic planning is a derived generalization that considers the separation of planning horizon into several stages and answering the questions of what, where, and when to install the network additions [1]. However, this paper focuses only on the static planning. In the past decade many researchers proposed various techniques to solve both static and dynamic planning problems. The literatures of mathematical model applied to TSEP were classified exclusively by *Latorre et al.* [2]. *Garver* [3] and *Villasana et al.* [4] proposed linear programming algorithms to solve the static TSEP. In dynamic view, *Escobar et al.* [5] proposed an efficient genetic algorithm (GA) to solve the problem of multistage and coordinated TSEP. Many artificial intelligence (AI) methods have been applied for solving TSEP problems. These methods include Simulated Annealing (SA) [6], Genetic Algorithm GA [5] and Tabu Search (TS) [7]. Recently, a method so called Ant Colony Optimization (ACO) has become a candidate for many potential applications. The ACO algorithm is inspired by the behaviors of real ant colonies and was first introduced by *Marco Dorigo* to solve the Traveling Salesman Problem (TSP) [8]. and later was applied to the asymmetric TSP [9], the Quadratic Assignment Problem (QAP) [10] and the Vehicle Routing Problem (VRP) [11]. Recently, ACO has been adapted to some network problems e.g. power distribution and communication network design [14]. This paper, therefore, proposes the application of ACO to solve the static TSEP based on DC power flow model. The results obtained by ACO are compared with conventional Genetic Algorithm (GA) method in term of solution quality and computational efficiency.

The remaining part of this paper is organized as follows. Section 2 gives the problem formulation of TSEP problem based on DC load flow model. Section 3 presents the principle of ACO algorithm. Section 4 presents the detailed procedures of the ACO approach for solving the TSEP problem. Section 5 shows a case study and gives the comparative results with the traditional methods. Conclusion is finally given in Section 6.

## 2. Problem Formulation

### 2.1 Objective Function

The objective function of TSEP is to minimize the investment cost of new transmission lines associated with physical and economic constraints. In this paper, the classical DC power flow model is used for static TSEP, which can be formulated as follow [13].

$$\text{Minimize} \quad C_T = \sum_{i,j\in\Omega} c_{ij} n_{ij} \tag{1}$$

where $C_T$ is the total investment cost of new transmission lines, $c_{ij}$ is the cost of a circuit which is a candidate for addition to the rights-of-way $i-j$, $n_{ij}$ is the number of circuit added to the rights-of-way $i-j$ and $\Omega$ is the set of all rights-of-way.

### 2.2 Constraints

#### 2.2.1 Equality constraint.

The set of equations determined by Kirchoff's laws (KCL, KVL) and the power flows in the system are expressed as:

**(a) Power Balance**

This constraint represents the conservation of power in each node.

$$\mathbf{SP} + \mathbf{P_G} - \mathbf{P_D} = 0 \tag{2}$$

Based on the above assumptions, DC load flow can be obtained as following equation.

$$P_i = \sum_{j=1}^{N} B_{ij}(\theta_i - \theta_j) \tag{3}$$

where $\mathbf{S}$ is the branch-node incidence matrix, $P_i$ is the real power flow injection at bus $i$, $\mathbf{P_G}$ is generation injection vector of nodes, $\mathbf{P_D}$ is the load demand vector of nodes, $B_{ij}$ is the lines susceptance matrix between bus $i-j$, $\theta_i, \theta_j$ is the phase angle of bus $i$ and bus $j$, $N$ is the total number of bus in system.

**(b) Kirchoff's voltage law (KVL)**

This constraint is the conservation of energy in the equivalent DC network and the constraint is nonlinear.

$$P_{ij} - B_{ij}(n_{ij}^0 + n_{ij})(\theta_i - \theta_j) = 0 \qquad (4)$$

where $P_{ij}$ is the power flow in branch $i-j$, $n_{ij}^0$ is the number of circuits in the original base system, $n_{ij}$ is the new number of circuits added to the rights-of-way $i-j$.

**2.2.2 Inequality constraint.**

The inequality constraints reflect the limits on physical devices in the power system as well as the limits created to ensure system security.

**(a) Transmission capacity limit.**

These constraints can represent the maximum power of transmission line which is capable of carrying based on thermal and dynamic stability considerations.

$$\left|P_{ij}\right| \le (n_{ij}^0 + n_{ij}) \cdot P_{ij}^{\max} \qquad (5)$$

where $P_{ij}^{\max}$ is the maximum power flow in the branch $i-j$.

**(b) Power generating limit.**

These constraints give the maximum and minimum generating capacities, outside of which it is not feasible to generate due to technical or economic reasons.

$$\mathbf{P_G^{\min}} \le \mathbf{P_G} \le \mathbf{P_G^{\max}} \qquad (6)$$

where $\mathbf{P_G^{\min}}$ and $\mathbf{P_G^{\max}}$ are the minimum and maximum generation injection vector of nodes.

**(c) Rights of way limit.**

For transmission planning, planners need to know the exact location and capacity of the new required lines. Therefore this constraint has to be included to consider in the planning. Mathematically, this constraint defines the line location and the maximum number of lines that can be installed in a specified location. It is represented as follow:

$$0 \le n_{ij} \le n_{ij}^{\max} \qquad (7)$$

where $n_{ij}^{\max}$ is the maximum new number of circuits added to the rights-of-way $i-j$.

## 3. Ant Colony Optimization

Inspired by the collective behavior of a real ant colony, *Marco Dorigo* first introduced the ant system (AS) in his Ph.D. thesis in 1992, and further published in [8, 9]. The characteristics of an artificial ant colony include positive feedback, distributed computation, and the use of a constructive greedy heuristic. Positive feedback accounts for rapid discovery of good solutions, distributed computation avoids premature convergence, and the greedy heuristic helps to find acceptable solutions in the early stages of the search process. In order to demonstrate the AS approach, the authors apply this approach to the classical TSP, asymmetric TSP, Quadratic Assignment Problem (QAP), and Job-Shop Scheduling problem (JSSP). The AS shows very good results in each applied area. More recently, *Dorigo and Gambardella* [9] have been working on extended versions of the AS paradigm. ACO is one of the extensions and has been applied to the symmetric and asymmetric TSP with excellent results in literature. The Ant System approach has also been applied successfully to other combinatorial optimization problems such as the vehicle routing problem.

ACO is an algorithm which was inspired by the behavior of real ants. Ethnologists have studied how blind animals such as ants capable of finding the shortest path from food sources to the nest without using visual cues. They are also capable of adapting themselves in the changing environment. For example, 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 communicating information among individuals regarding path to decide the direction. Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one.

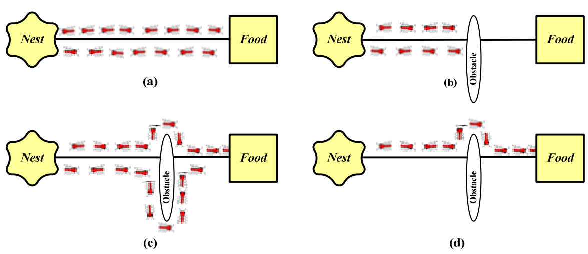


Fig. 1 Behavior of real ants colony

Fig.1 illustrated the searching behavior of Ant family. In Fig.1(a) ants are on a straight line that connects a food source to their nest. An ant will deposit pheromone while walking and it probabilistically prefers to follow a direction rich in pheromone. This behavior can be explained how ants can find the shortest path that reconnects a line broken by an obstacle. In Fig. 1 (b). ants are obstructed and they can not continue to go. Therefore, they have to choose between turning right or left. Half of the ants choose to turn right and the other half choose to turn left. A similar situation arises on the other side of the obstacle shown in Fig. 1 (c). Ants choosing the shorter path will more rapidly reconstitute the interrupted pheromone trail compared with those choosing the longer route. Thus, the shorter path will receive a greater amount of pheromone per time unit and, in turn, lager number of ants will choose the shorter one. Due to this positive feedback, all the ants will rapidly choose the shorter path shown in Fig. 1 (d). All ants move at approximately the same speed and deposit a pheromone trail at approximately the same rate. The time consumed on the longer side of an obstacle is greater than the shorter one. It thus makes the pheromone trail accumulate more quickly on the shorter side. Ants prefer higher pheromone trail levels causing the accumulation to build up faster on the shorter route.

## 4. Implementation for ACO for TSEP

This section elaborates an application of ACO algorithm to solve TSEP. First, the model has to be formulated as the routes between nest and food source for ACO. For example, a power system consists of 3 buses and 3 branches. Each branch can choose a number of possible line and the possible rights-of-way as shown in Fig. 2. This network can be graphically translated as the radial routes between nest and food source for ACO as shown in Fig. 3. This model reveals that the transmission system topology can be constructed by randomly selecting the number of circuit(s) of each branch, which is similar to the ant's route between the nest and food source.

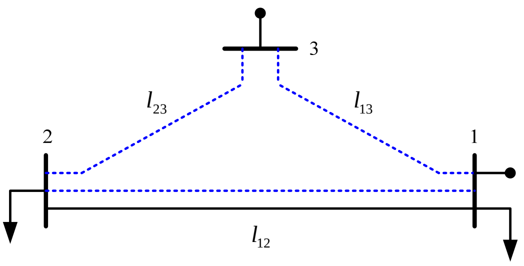


Fig. 2 Example of power system 3 buses 3 branches.

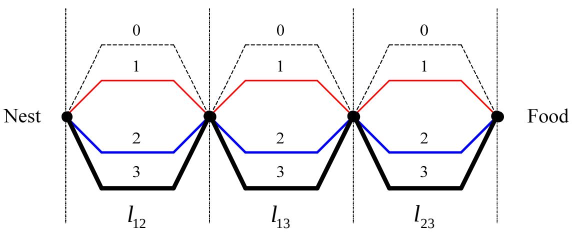


Fig. 3 Simulate model as the routes of ants between nest and food source.

In general, the procedure of ACO algorithm can be described as follows: $m$ ants are initially positioned at the nest. Each ant will choose a possible route as a solution. In fact, each ant builds a feasible solution (called a tour) by repeatedly applying a stochastic greedy search, called, the state transition rule. Once all ants have terminated their tours, the following steps are performed: The amount of pheromone is modified by applying the global updating rule [8], [9]. Ants are guided, in building their tours, by both heuristic and pheromone information. Naturally, a link with a high amount of pheromone is a desirable choice. The pheromone updating rules are designed so that they tend to give more pheromone to edges, which should be visited by ants. A flowchart of the proposed TSEP-ACO and its algorithm is shown in Fig. 4. The detail of ACO algorithm can be described in the following steps.

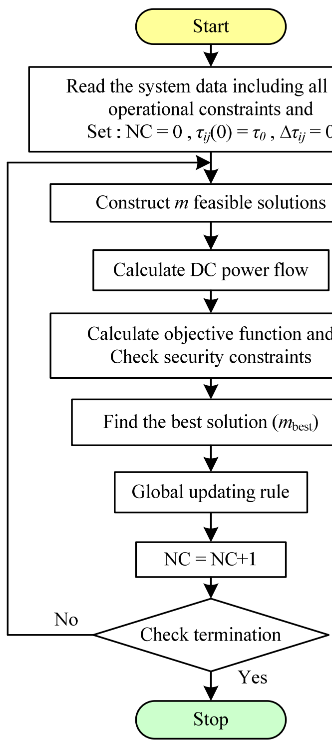


Fig. 4 Flow chart of TSEP-ACO algorithm.

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**Step 1. Initialization**

Set NC = 0 /* NC: Cycle Counter */

**For** every combination $(i, j)$

Set an initial value $\tau_{ij}(0) = \tau_0$ and

$\Delta\tau_{ij} = 0$

**End**

**Step 2. Construct feasible solutions**

**For** k=1 to m /* m: number of ants */

**For** i=1 to n /* n: number circuit of branch*/

Choose a level of connection with transition probability give by Eq. (8).

**End**

Calculate Objective Function Eq. (1) and Check Constraints Eq. (2-7)

**End**

Display the best solution of each ant

Chosen the best of ant colony

Update the best solution.

**Step 3 Global updating rule**

**For** every combination $(i, j)$

**For** k=1 to m

Find $\Delta\tau_{ij}^{k}$ according to Eq. (12)

**End**

Update $\Delta\tau_{ij}$ according to Eq. (11).

**End**

Update the trail values according to Eq. (10).

Update the transition probability according to Eq. (8).

**Step 4. Next search**

Set NC = NC+1

**For** every combination $(i, j)$

$\Delta\tau_{ij} = 0$

**End**

Choose a level of connection with transition probability give by Eq. (8).

Calculate Objective Function Eq. (1) and Check Constraints Eq. (2-7)

**Step 5. Termination**

**If** (NC < $NC_{max}$)

**Then**

Go to step 2, **Else**

Print the best feasible solution

Stop

**End**

**End**

### 4.1 State transition rule

The state transition probability rule of the ant colony is given in Eq. (8). This equation represents the probability that each ant $(k)$ selects a number circuit in branch $i-j$.

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{i=1}^{m}\left[\tau_{im}(t)\right]^{\alpha}\left[\eta_{im}(t)\right]^{\beta}} \tag{8}$$

where $\tau_{ij}$ is the pheromone intensity and $\eta_{ij}$ is the heuristic information between node $i$ and node $j$, respectively. In addition, $\alpha$ is the relative importance of the trail and $\beta$ is the relative importance of the heuristic information. The problem specific heuristic information in this paper is:

$$\eta_{ij} = \frac{1}{c_{ij}} \tag{9}$$

where $c_{ij}$ represents the associated cost of constructions transmission lines. Therefore, the number circuit with lesser cost has greater probability to be chosen.

### 4.2 Global updating rule

During the solution construction, it is no guarantee that an ant will construct a feasible solution, which obeys the reliability constraint. The pheromone updating treats the unfeasible solution. The amount of pheromone, deposited by ants, is set to a high value if the generated solution is feasible. On other hand, this value is set to a low value if it is infeasible. Therefore, this value depends on the solution quality. Infeasibility can be handled by assigning the penalty which proportion to the amount of reliability violations. In case of feasible solution, an additional penalty is introduced to improve its quality. Following the above remarks, the trail intensity is updated as follows:

$$\tau_{ij}(t) = (1-\rho)\cdot(\tau_{ij}(t-1)) + \Delta\tau_{ij} \qquad (10)$$

$\rho$ is a coefficient such that $(1-\rho)$ represents the evaporation of trail and $\Delta\tau_{ij}$ is:

$$\Delta\tau_{ij} = \sum_{k=1}^{m}\Delta\tau_{ij}^{k} \qquad (11)$$

where $m$ is the number of ants and $\Delta\tau_{ij}^{k}$ is given by:

$$\Delta\tau_{ij}^{k} = \begin{cases} 1 & \text{if } \mathrm{k}^{\mathrm{th}} \text{ ant chooses path} \\ 0 & \text{otherwise} \end{cases} \qquad (12)$$

### 5. Numerical Results

The proposed TSEP-ACO method was tested on the 18 bus of China Southwest system [15]. The 18-bus of China Southwest system has 18 buses and 27 candidate branches. The total demand is 2,066 MW and maximum possible number of added lines (rights-of-way limit) per branch equals four. The optimal planning solution for the 18 bus of China Southwest system is $n_{1\text{-}11}$ = 1, $n_{4\text{-}16}$ = 1, $n_{5\text{-}12}$ = 1, $n_{6\text{-}14}$ = 2, $n_{7\text{-}8}$ = 1, $n_{7\text{-}13}$ = 1, $n_{8\text{-}9}$ = 1 $n_{9\text{-}10}$ = 2, $n_{14\text{-}15}$ = 1, $n_{16\text{-}17}$ = 2, $n_{17\text{-}18}$ = 1. The simulation was made in comparison to GA approach. All methods are performed 30 trials, under the same evaluation function and individual definition, in order to compare their solution quality, convergence characteristic, and computation efficiency. The programs were implemented by MatLab® languages on Intel® Core2 Duo 1.66 GHz Laptop with 2 GB RAM under Windows XP. The statistic results which are performed by 30 trials, such as the investment cost, standard deviation, computational time and percentage of approaching near optimal solution, are shown in Table 1.

Fig.5. shows the comparative convergence characteristic of the ACO and GA Fig.6 shows the distribution outlines of the best solution of each trial. Almost all investment costs obtained by the ACO method are lower. This verifies that the ACO method has better quality of solution.

Table 1: Results of 18 bus of China Southwest system

| Results of static TEP | Method | |
|---|---|---|
| | ACO | GA |
| Best cost (×$10^3$ US$) | 40,375 | 40,375 |
| Average cost (×$10^3$ US$) | 40,475 | 41,037.5 |
| Worst cost (×$10^3$ US$) | 41,375 | 45,175 |
| Standard deviation | 305.13 | 1,245.52 |
| Average CPU Time (sec.) | 73.1 | 120.86 |
| Line addition for the best result | $n_{1\text{-}11}$ = 1, $n_{4\text{-}16}$ = 1, $n_{5\text{-}12}$ = 1, $n_{6\text{-}14}$ = 2<br>$n_{7\text{-}8}$ = 1, $n_{7\text{-}13}$ = 1, $n_{8\text{-}9}$ = 1 $n_{9\text{-}10}$ = 2<br>$n_{14\text{-}15}$ = 1, $n_{16\text{-}17}$ = 2, $n_{17\text{-}18}$ = 1 | |

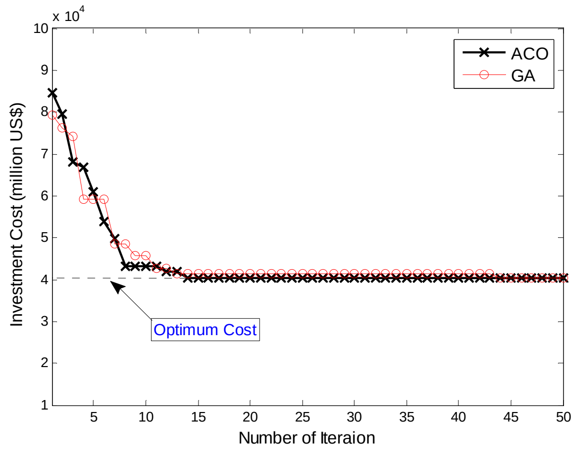


Fig.5. Convergence characteristic of three methods.

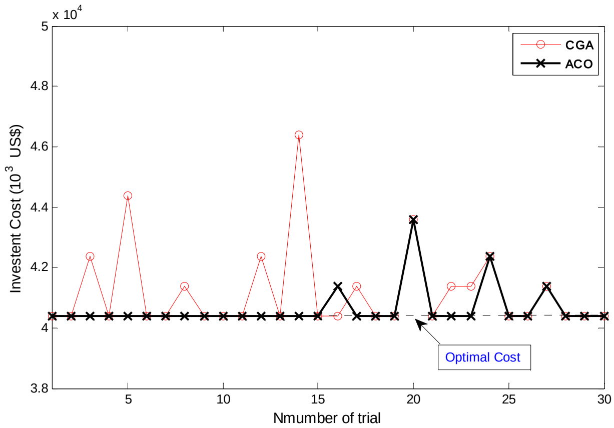


Fig.6. Distribution of investment cost of three methods.

## 6. Conclusion

This paper proposes a novel approach adopting ACO search algorithm to solve TSEP problem that works corporately with the DC power flow model. The proposed method is test with 18 bus of China Southwest system which demonstrates good performance in comparison to the GA method in terms of less calculation time, quality of solution and stable-convergence characteristic.

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