K. Y. Lee and M. A. El-Sharkawi (Editors), IFAC Tutorial on Evolutionary Computation Techniques for Power System Optimization, Seoul, Korea, Sept. 15-18, 2003. K. Y. Lee and M. A. El-Sharkawi (Editors), Modern Heuristic Optimization Techniques, Chapter 5, pp. 89-100, Wiley-Interscience, 2008.

Chapter 6

Ant Colony Search Algorithms in Power System Optimization

Abstract: This chapter presents a novel co-operative agents approach, Ant Colony Search Algorithm (ACSA). The main purpose of this chapter is to introduce the applicability of an alternative intelligent search method in power system optimization. The ACSA is derived from the theoretical biology on the topic of ant trail formation and foraging methods. In the ACSA, the state transition rule, global and local updating rules are also introduced to ensure the optimal solution. Once all ants have completed their tours a global pheromone updating rule is then applied and the process is iterated until the stop condition is satisfied. The effectiveness of the proposed scheme has been demonstrated on the daily generation scheduling problem of model power systems.

Index Terms: Ant colony search algorithm, optimization, short-term generation scheduling, combined heat and power dispatch.

1. INTRODUCTION

There are a large number of different combinatorial optimisation problems facing electricity utilities. The deregulation of electricity supply industry world-wide adds ever growing motivations to develop new optimisation algorithms so as to design best strategies for most effectively utilising the asset under increasing commercial pressure. Various algorithmic and heuristic approaches [1 - 3] have been adopted or investigated by power engineers. These include lambda-iteration method, the gradient method, Lagrangian relaxation, benders decomposition, interior point method, linear programming and dynamic programming etc. More recently heuristic techniques such as artificial neural networks, simulated annealing, tabu-search and evolutionary computing have also been intensively investigated. In particular, for the last few years there has been a growing interest in algorithms inspired by the observation of natural phenomena to help solve complex computational problems. In this chapter, a novel co-operative agent algorithm, Artificial Ant Colony Search Algorithm (ACSA), which was inspired by the observation of the behaviour of ant colonies is investigated. Ant Colony Search Algorithms (ACSAs) have recently been introduced as powerful tools to solve the order based problems such as travelling salesman problem (TSP) and quadratic assignment problem [4]. This chapter presents feasibility studies of its potential applications in power systems carried [5 – 8].

2. ANT COLONY ALGORITHM

It will be useful to understand how ants, which are almost blind animals with very simple individual capacities acting together in a colony, can find the shortest route between the ant's nest and a source of food.

2.1. Behavior of Real Ants

The ant colony search algorithms mimic the behaviour of real ants. As is well known, real ants are capable of finding shortest path from food sources to the nest without using visual cues. They are also capable of adapting to changes in the 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 ants have 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. 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.

The process can be clearly illustrated by Fig. 1. In Figure 1a ants are moving on a straight line which connects a food source to the nest. Once an obstacle appears as shown in Fig. 1b, the path is cut off. Those ants that are just in front of the obstacle cannot continue to follow the pheromone trail and therefore it can be expected that they have the same probability to turn right or left. In Fig. 1c, these ants that choose by chance the shorter path around the obstacle will more rapidly reconstitute the interrupted pheromone trail compared to those that choose the longer path. Hence, the shorter path will receive a higher amount of pheromone in the time unit and this will in turn cause a higher number of ants to choose the shorter path. Due to this positive feedback (autocatalytic) process, very soon all ants will choose the shorter path.

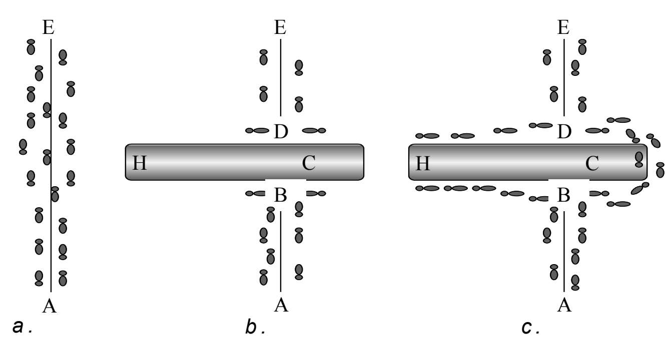

Fig. 1. The behaviour of real ants. (a) ants travel the shortest path; (b) an obstacle breaks the path; (c) ants choose the sorter path.

K. Y. Lee and M. A. El-Sharkawi (Editors), IFAC Tutorial on Evolutionary Computation Techniques for Power System Optimization, Seoul, Korea, Sept. 15-18, 2003. K. Y. Lee and M. A. El-Sharkawi (Editors), Modern Heuristic Optimization Techniques, Chapter 5, pp. 89-100, Wiley-Interscience, 2008.

2.2. A Simple Ant Colony Algorithm

The structure of the simple Ant Colony Search Algorithm is shown in Fig. 2. It has the following major steps:

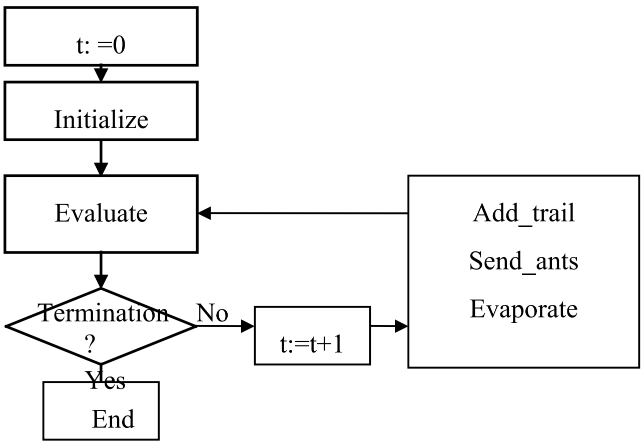

Fig. 2. Structure of simple ACSA.

- (1) Initialize A(t): The parameters to be optimized are encoded as a real number. Before each run, the initial populations (Nest) of the colony are generated randomly within the feasible region which will crawl to different directions at a radius not greater than R.

- (2) Evaluate A(t): The fitness of all ants are evaluated based on their objective function.

- (3) Add_trail: Trail quantity is added to the particular directions the ants have selected in proportion to the ants' fitness.

- (4) Send_ants A(t): According to the objective function, their performance will be weighed as fitness value which influences the level of trail quantity addition to the particular directions the ants have selected. Each ant chooses the next node to move taking into account two parameters: the visibility of the node and the intensity of trail previously laid by other ants. The send_ants operation sends ants by selecting directions using Tournament selection based on the two parameters. The k-th ant starting from node i decides to move to node j on the basis of probability p_{ij}^k defined as follows:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum\limits_{k \in allowed_k}\left[\tau_{ik}\right]^{\alpha} \cdot \left[\eta_{ik}\right]^{\beta}} & \text{if } j \in \text{allowed}_k \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where: visibility,

$$\eta_{ij} = \left|\mu - \Delta F\right| \tag{2}$$

Move value, ΔF = original total cost - new total cost

μ, α, β are the heuristically defined parameters. μ is used for cost setting, 0< α <1 is a pheromone decay parameter and β is a parameter which determines the relative importance of pheromone versus distance.

Intensity trail, $\tau_{ij}(t)$ on edge (i,j) at time t. Each ant at time t chooses the next node, where it will be at time t+1. For 1 iteration of ant colony search algorithm, m moves are carried out by m ants in the interval (t, t+1), then for every n iterations of the algorithm each ant has completed a tour. At this point the trail intensity is updated as:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij} \tag{3}$$

where: ρ is a coefficient of persistence of the trail during a cycle which is heuristically defined.

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k \tag{4}$$

where: $\Delta\tau_{ij}^k$ is the quantity of substance laid on edge (i,j) by the k-th ant between time t and t+n.

- (5) Evaporate: Finally, the pheromone trail secreted by an ant eventually evaporates and the starting point (nest) is updated with the best tour found.

2.3. Major Characteristics of Ant Colony Search Algorithm

There are some attractive properties of ant colony search algorithm when compared with other methods:

Distributed Computation - Avoid Premature Convergence: Conventionally, scientists choose to work on system simplified to a minimum number of components in order to observe essential information. Ant colony search algorithm often simplifies as much as possible the components of the system, for the purpose of taking into account their large number. The power of the massive parallelism in ACSA is able to deal with incorrect, ambiguous or distorted information which are often found in nature. The computational model contains the dynamics which is determined by the nature of local interactions between many elements (artificial ants).

Positive Feedback - Rapid Discovery of Good Solution: The unique inter-ant communication involves a mutual information sharing while solving a problem. Occasionally, the information exchanged may contain errors and should alter the behaviour of the ants receiving it. As the search proceeds, the new population of ants often containing the states of higher fitness will affect the search behaviour of others and will eventually gain control over other agents while at the same time actively exploiting inter-ant communication by mean of the pheromone trail laid on the path. The artificial ant foraging behaviour dynamically reduces the prior uncertainty about the problem at hand. As ants doing a task can be either "successful" or "unsuccessful" they can switch between these two according to how well the task is performed. Unsuccessful ants also have a certain chance to switch to be inactive, and successful ants have a certain chance to recruit inactive ants to their task. Therefore, the emerging collective effect is in a form of autocatalytic behaviour, in that the more ants following a particular path, the more attractive this path becomes for the next ants that meet. It can give rise to global behaviour in the colony.

Use of Constructive Greedy Heuristic - Find Acceptable Solutions In The Early Stage of The Process: Based on the available information collected from the path (pheromone trail level and visibility), the decision is made at each step as a constructive way by the artificial ants, even if each ant's decision always remains probabilistic. It tends to evolve a group of initial poorly generated solution to a set of acceptable solutions through successive generations. It uses objective function to guide the search only, and does not need any other auxiliary knowledge. This greatly reduces the complexity of the problem. The user only has to define the objective function and the infeasible regions (or obstacle on the path).

3. CASE STUDIES

3.1. Case Study 1 - Short-Term Generation Scheduling Technique of Thermal Units

To supply a high quality of electric energy to the consumer in a secure and economic manner, electric utilities face many economical and technical problems in operation, planning and control of electric energy systems. One of the major problems is to determine the most economic and secure way of short-term generation scheduling and dispatch under given constraints. Various approaches were proposed for solving the short-term generation scheduling problems [10].

The main objective of the short-term generation scheduling problem is to determine the output of thermal units so as to obtain a minimum total cost over a period of 24 hours subject to a set of constraints, which arise from the system security requirements and restrictions on the operation of the units. The objective function to be minimized can be written as

Minimiz

$$F = \sum_{j=1}^{T}\left[\sum_{i\in G} f_i(P_{ij}) + C(j,k)\right] \tag{5}$$

where, G : number of generating units
T : the time horizon of interest (24 hours)

$$f_i = a_i + b_i P_{ij} + c_i P_{ij}^2 \,[\hbar / hr] \tag{6}$$

P_{ij} : real power output of the ith unit in the jth stage

$$C(j,k) \in \{C_T(j,k), C_P(j,k)\} \tag{7}$$

$C_T(j,k)$, $C_P(j,k)$: transition and penalty cost from stage j to k

Subject to:

(a) real power balance constraint

$$\sum_{i\in G} P_{ij} = P_{Dj} + P_{Lj} \quad , j \in T \tag{8}$$

where, P_{Dj}, P_{Lj} are the total demand and the transmission loss in the area at the jth stage.

(b) real power operating limits of generating units

$$P_i^{\min} \le P_{ij} \le P_i^{\max} \quad , i \in G, j \in T \tag{9}$$

where, $P_i^{\min}, P_i^{\max}$ are the minimum and the maximum real power outputs of the ith unit

(c) spinning reserve constraint

$$\left(\sum_{i=1}^{G} u_{ij} P_i^{\max} - P_{Dj}\right) / P_{Dj} \ge 0.1, j \in T \tag{10}$$

where, u_{ij} is the status index of the ith unit at the jth stage (1 for up and 0 for down).

(d) minimum up time of units

K. Y. Lee and M. A. El-Sharkawi (Editors), IFAC Tutorial on Evolutionary Computation Techniques for Power System Optimization, Seoul, Korea, Sept. 15-18, 2003. K. Y. Lee and M. A. El-Sharkawi (Editors), Modern Heuristic Optimization Techniques, Chapter 5, pp. 89-100, Wiley-Interscience, 2008.

$$(u_{ij} - u_{i,j-1})(w_{i,j-1} - \tau h_i) \le 0, i \in G, j \in T \quad (11)$$

where, τh_i is the minimum up time of the ith unit and

$$w_i = u_{ij}(w_{i,j-1} + 1) \quad (12)$$

(e) minimum down time of units

$$(u_{ij} - u_{i,j-1})(q_{i,j-1} - \tau l_i) \ge 0, i \in G, j \in T \quad (13)$$

where, τl_i is the minimum down time of the ith unit and

$$q_{ij} = (1 - u_{ij})(q_{i,i-1} + 1) \quad (14)$$

(f) maximum operating time of units

$$u_{ij,}(v_{i,j-1} - \tau u_i) \le 0, i \in G, j \in T \quad (15)$$

where, τu_i is the maximum operating time of the ith unit and

$$v_{ij} = u_{ij}(v_{i,j-1} + 1) \quad (16)$$

To consider all the constraints mentioned above, the generation scheduling problem could be modelled in a form of dynamic process as follows.

$$F_j({}^jU^l) = Min.\{\Phi_j^l({}^{j-1}U^k, {}^jU^l)\}, j \in T \quad (17)$$

Subject to the constraints (a) -(f)
where,

$$\Phi_j^l({}^{j-1}U^k, {}^jU^l) = \sum_{i \in G} f_i(P_{ij}) + \sum_{i \in G} SC_i(q_{i,j-1}) + \sum_{i \in G} DC_i + C_P(k,l) + F_{j-1}({}^{j-1}U^k) \quad (18)$$

Equation (17) is the minimal total operational cost to arrive at the state $({}^jU^l)$ from $({}^{j-1}U^k)$. In equation (18), the first, second and third terms represent the total production fuel cost of a state, start-up and shut-down costs of units, respectively. The fourth term represents the penalty cost imposed when any of transition constraints are violated, and the last term is the minimum total accumulated cost to reach to the state $({}^jU^l)$ from the initial stage. The constraints represented by (a) - (f) will be treated in different ways. The operational constraints (a), (b) and (c) are handled using conventional economic load dispatch module for each state while the search space is being formed, and the transition constraints (d), (e) and (f) will be considered during the process of state transition by the dynamic programming (DP) based conventional method to get reference results, and the ACSA based technique to obtain final solution results. The penalty cost will also be applied for the violated transition constraints in the same process. Here, the solution procedure should be slightly modified so that the ACSA can easily be adopted. The ACSA works in this application, combined with the DP process, as follows:

- form the travelling salesman type of search space for the Generation Scheduling Problem (GSP)
- *m* ants are initially positioned on *n* states chosen according to some initialisation rule
- each ant builds a tour by repeatedly applying the state transition rule
- while constructing its tour, an ant changes the amount of pheromone on the visited edges by applying the local updating rule
- once all ants have terminated their tour, the amount of pheromone modified again by applying the global updating rule
- seek the best tour using the solution process, in which ants are guided in building their tours by both heuristic information and by pheromone information. An edge with a high amount of pheromone is a very desirable choice
- the pheromone updating rules are designed so that they tend to give more pheromone to edges which should be visited by ants

The overall flow of the proposed ACSA based technique for GSP is briefly given in Figure 3

K. Y. Lee and M. A. El-Sharkawi (Editors), IFAC Tutorial on Evolutionary Computation Techniques for Power System Optimization, Seoul, Korea, Sept. 15-18, 2003. K. Y. Lee and M. A. El-Sharkawi (Editors), Modern Heuristic Optimization Techniques, Chapter 5, pp. 89-100, Wiley-Interscience, 2008.

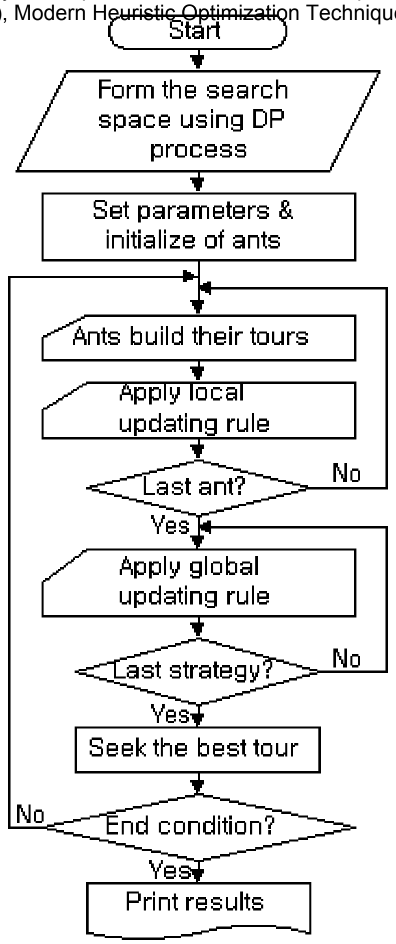

Fig. 3. Flow of ACSA based technique.

This proposed method deals with a 24-hour generation scheduling or allocation problems. Application results of the proposed algorithm to 6-unit model power system are presented. The system data are given in ref [7].

Figure 4 shows the generation schedules the total capacity of the 6-unit system obtained by the two algorithms, Hybrid Dynamic Programming (HBDP) and ACSA. The difference in the generation cost is illustrated in Figure 5, and the total generation cost of the two methods are $187,116.7 for HBDP and $184,841.5 for ACSA, respectively. All the results show that ACSA can achieve almost the same results as obtained by the HBDP.

.

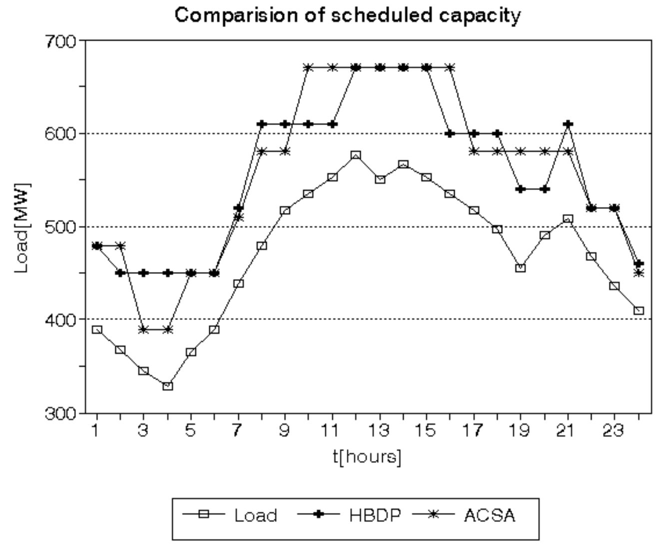

Fig. 4. Comparison of scheduled total capacities

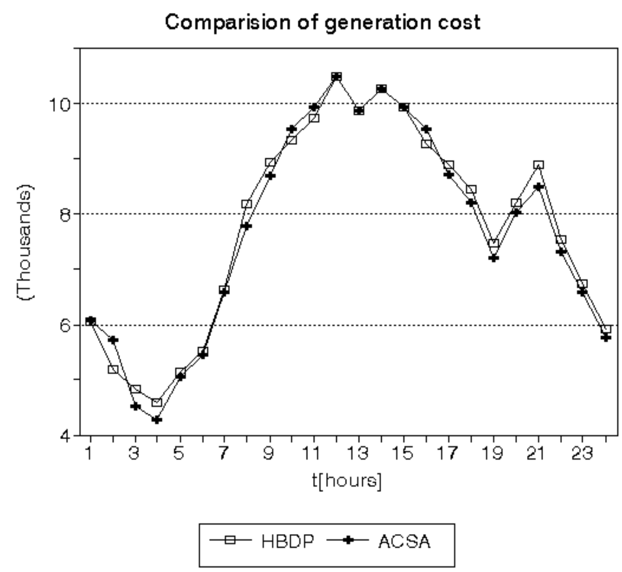

Fig. 5. Comparison of generation costs of the 6-unit system.

3.2 Case Study 2 - Combined Heat and Power Dispatch

Combined heat and power (CHP) generation is an established and mature technology which has energy efficiency and environmental advantages over other forms of energy supply. The benefits of real-time optimization of power generation and CHP can be significant. However, the multiple-demand and the mutual dependencies of heat-power capacities introduce a complication in integrating co-generation units into the power system economic dispatch.

The combined heat and power dispatch problem in a system is to determine the unit heat and power production so that the system production cost is minimized while the heat and power demands and other constraints are met. The power outputs of electricity units and heat units are restricted by their own upper and lower limits. The CHP dispatch problem can be formulated as follows:

Minimize

$$\sum_{i=1}^{n_p} c_i(p_i) + \sum_{j=1}^{n_c} c_j(h_j, p_j) + \sum_{k=1}^{n_h} c_k(h_k) \quad (19)$$

Subject to

$$\sum_{i=1}^{n_p} p_i + \sum_{j=1}^{n_c} p_j = p_d \quad (20)$$

$$\sum_{j=1}^{n_c} h_j + \sum_{k=1}^{n_h} h_k = h_d \quad (22)$$

$$p_i^{\min} \le p_i \le p_i^{\max}, i = 1,\ldots,n_p \quad (23)$$

$$p_j^{\min}(h_j) \le p_j \le p_j^{\max}(h_j), j = 1,\ldots,n_c \quad (24)$$

$$h_j^{\min}(p_j) \le h_j \le h_j^{\max}(p_j), j = 1,\ldots,n_c \quad (25)$$

$$h_k^{\min} \le h_k \le h_k^{\max}, k = 1,\ldots,n_h \quad (26)$$

where c is the unit production cost; p is the unit power generation; h is the unit heat production; h_d , p_d are the system heat and power demands; *i, j* and *k* are the indices of conventional power units, co-generation units and heat-only units respectively; n_p, n_c and n_h are the corresponding numbers of the types of units ; p^{min} , p^{max} , h^{min} and h^{max} are the minimum and maximum unit power capacity and heat capacity limits, respectively.

In the heat-power feasible operation region of a combined cycle co-generation unit, the power outputs and heat outputs are restricted by their own upper and lower limits which in some states changing one would affect the other. It is obvious that the complication arising in the CHP economic dispatch is the mutual dependencies of extra constraints than in pure economic dispatch.

A test system containing a set of 4 generators [8] is used to illustrate the performance of the proposed method. Unit 1 is for power generation only and unit 4 for heat generation only. Units 2 and 3 are co-generation units. The corresponding production cost functions are given below.

$$c_1 = 50 p_1 \quad (27)$$

$$c_2 = 2650 + 14.5 p_2 + 0.0345 p_2^2 + 4.2 h_2 + 0.03 h_2^2 + 0.031 p_2 h_2 \quad (28)$$

$$c_3 = 1250 + 36 p_3 + 0.0435 p_3^2 + 0.6 h_3 + 0.027 h_3^2 + 0.011 p_3 h_3 \quad (29)$$

$$c_4 = 23.4 h_4 \quad (30)$$

The constraints for units 1 and 4 are

$$0.0 \le p_1 \le 150 MW \quad (31)$$

$$0.0 \le h_4 \le 2695.2 MWth \quad (32)$$

And the constrains for units 2 and 3 are defined in Figs. 6 and 7.

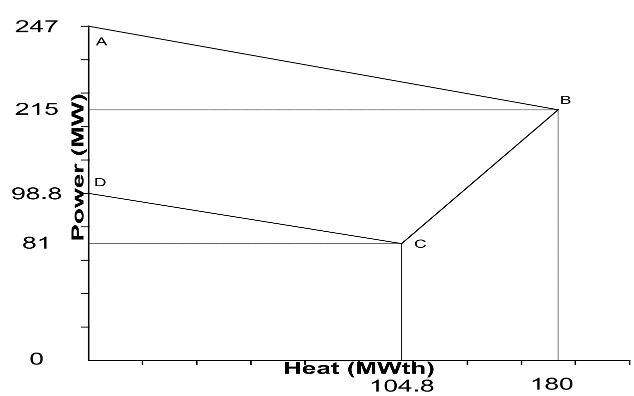

Fig. 6. Heat-power feasible region for the co-gen. unit 2.

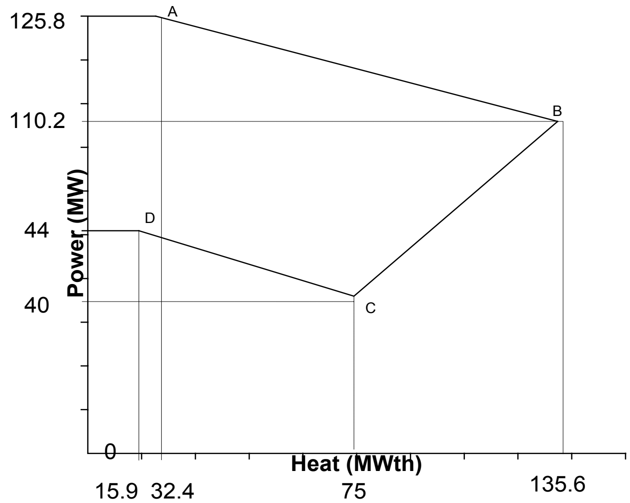

Fig. 7. Heat-power feasible region for the co-gen. unit 3.

The following ACSA parameters are chosen for this particular problem:

Number of ants =10; Max Generation number=100; Number of intermediate steps=5, α = 0.5, β = 0.05, μ = 10, ρ = 0.5, Q = 50.

The ACSA decomposes the problem into 2-stages [1], the outer layer contains the power dispatch which is solved by the ACSA. The inner layer solves the heat dispatch with the unit heat capacity limits passed by the outer layer. The binding constraints in the heat dispatch solution are, therefore, fed back to the outer layer to modify the unit power incremental costs of co-generation units.

The system power and heat demands are 200MW and 115 MWth, respectively. Table 1 lists the results by reference [9] and the proposed method, which are close to each other. The evolutionary process illustrated in Figure 8 shows the collective behavior speeding up the whole process as the number of ant increases.

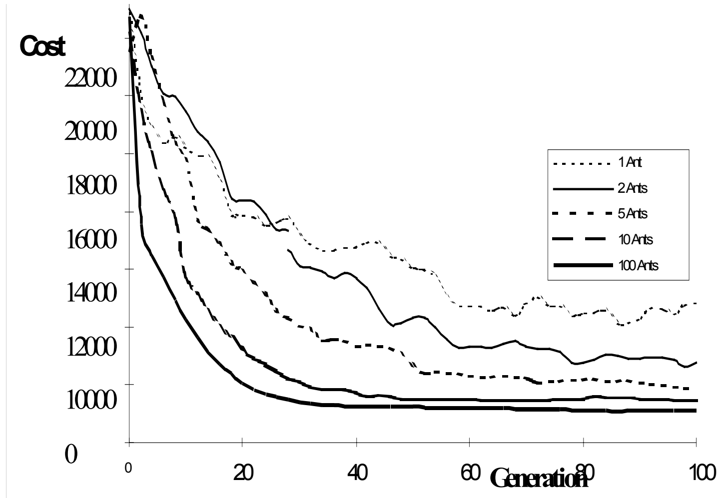

Fig. 8. Evolutionary process of ACSA for different number of population.

Table 1. Test Results in comparison with a GA-based approach.

	Unit 1 power	Unit 2 power	Unit 2 heat	Unit 3 power	Unit 3 Heat	Unit 4 heat	Total Power	Total Heat	Total Cost ($)
Ref. [9]	0.00	160.00	40.00	40.00	75.00	0.00	200.00	115.00	9527.00
ACSA	0.08	150.93	48.84	49.00	65.79	0.37	200.00	115.00	9452.20

4. CONCLUSIONS

This paper presents the applications of a search methodology - Ant Colony Search Algorithm - based on a distributed autocatalytic process. The individual ants are rather simple, however, the entire colony foraging towards the bait site can exhibit complicated dynamics resulting in a very attractive search capability. The results obtained clearly show the Ant Colony Search Algorithm converges to the optimum solution through an autocatalytic process. The massive parallel agent co-operation makes the ants able to jump over the local optimum and to identify the right cluster easily, hence, a good solution can be found. Its feasibility in power system optimization has been demonstrated in two examples.

5. REFERENCES

[1] Y.H. Song (ed.), Modern Optimisation Techniques in Power Systems, Kluwer Academic Publishers, 1999

[2] M.R. Irving, Y.H. Song, Optimisation techniques for electrical power systems, IEE Power Engineering Journal, Vol.14, No.5, 2000, pp245-254

[3] Y.H. Song, M.R. Irving, Optimisation techniques for electrical power systems Part 2 Heuristic optimisation techniques, IEE Power Engineering Journal, Vol.15, No.3, 2001, pp.151-160

[4] M. Dorigo, V. Maniezzo, A. Colorni, The Ant System: Optimisation by a colony of co-operating agents, IEEE Transactions on Systems, Man and Cybernetics Part B, 1996, **26**(1), 29-41

[5] Y.H. Song, C.S. Chou, Application of ant colony search algorithms in power system optimisation, IEEE Power Engineering Review, Vol.18, No.12, 1998, pp.63-64

[6] Y.H. Song, C.S. Chou, Y Min, Large-scale economic dispatch by artificial ant colony search algorithms, Electric Machines and Power Systems, Vol.27, No.5, 1999, pp.679-690

[7] I.K. Yu, Y.H. Song, a Novel short-term generation scheduling technique of thermal units using ant colony search algorithms, Electric Power and Energy Systems, Vol.23, 2001, pp.471-479

[8] Y.H. Song, C.S. Chou, T.J. Stonham, Combined heat and power economic dispatch by improved ant colony search algorithm, Electric Power Systems Research, Vol.52, 1999, pp.115-121.

[9] Y.H. Song, Q.Y. Xuan, Combined Heat and Power Economic Dispatch Using Genetic Algorithm Based Penalty Function Method, Electric Machines and Power Systems, Vol. 26, 1998, No.4

[10] K. Y. Lee, Y. M. Park and J. L. Ortiz, "A United Approach to Optimal Real and Reactive Power Dispatch," <u>IEEE Transaction on Power Apparatus and Systems</u>, Vol. PAS-l04, pp. ll47-ll53, May l985.