Journal of ELECTRICAL ENGINEERING, VOL. 55, NO. 3-4, 2004, 57–63

ANT COLONY OPTIMIZATION FOR NEW REDESIGN PROBLEM OF MULTI–STATE ELECTRICAL POWER SYSTEMS

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The most important phase in many industrial applications is the design problem. Usually the demand increases randomly with time in the form of a cumulative demand curve. To adapt the power system capacity to the demand a new design is predicted. This paper uses an ant colony optimization (ACO) method to solve the new redesign problem for multi-state series-parallel power systems. The study horizon is divided into several periods. A multiple-choice of components can be chosen and included into subsystem component at any stage to improve the system performance. The components are characterized by their cost, performance and availability. The objective is to minimize the investment over the study period while satisfying availability or performance constraints. A universal generating function technique is applied to evaluate power system availability. The ant colony approach is required to identify the optimal combination of components with different parameters to be allocated in parallel.

K e y w o r d s: new redesign, ant colony, multi-state, power system, universal generating moment function

1 INTRODUCTION

In many industrial systems, new systems designs have been considered as an important problem, *eg*, in power systems and in manufacturing systems. For instance, modifying the existing structure, designing a new structure and adding new components (reinforcement) belonging to the redundancy optimization problem (ROP) as suggested in (Levitin, Lisnianski, Ben-Haim and Elmakis, 1997). This latter is a well- known combinatorial optimization problem where the new design is achieved by numerous discrete choices made from components available on the market. Based on the cost, availability and performance, the objective function is to minimize the investment-costs over each study period within the planning horizon for a certain availability or (reliability) requirement. Figure 1 shows a typical series-parallel power structure. However, the capacity of many power production systems is defined by multiple heterogeneous units. In this situation the system can have several levels of performance: from perfect working to total failure. In this case it is considered as a *multi-state* system (MSS).

The MSS system consists of n subsystems C_i ($i = 1, 2, \ldots, n$) in series arrangement. Each subsystem C_i can contain several components of type i connected in parallel from various versions on the market. Each version in turn can contain one or more identical components in parallel. Components are characterized by their cost, availability and performance according to their version. Different versions of components may be chosen for any given subsystem. Besides, a lot of alternatives lead to a change in performance and reliability, such as series-parallel modernization as in (Levitin, 1999). The simplest method in this work to help system performance to face the increased demand is a new design.

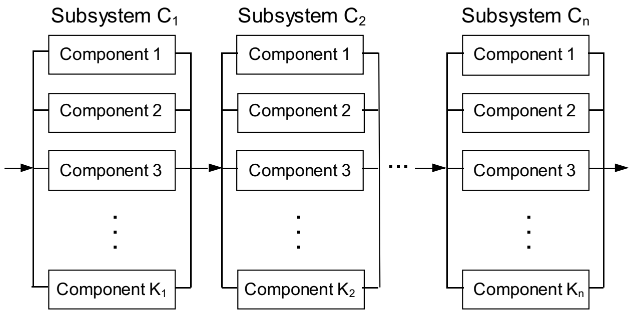

Fig. 1. Series-parallel power system structure

The classical reliability theory is based on the binary assumption that the system is either working perfectly or completely fails. However, in many real life situations we are actually able to distinguish among various levels of performance for systems. In this case, it is important to develop MSS reliability theory. Most of research works in MSS reliability analysis extend the results to the multi-state case. A recent review of the literature can be found in (Ushakov, Levitin and Lisnianski, 2002). Generally, the methods of MSS reliability assessment are based on four different approaches: (1) The structure function approach; (2) The stochastic process (Markov) approach; (3) The Monte-Carlo simulation technique; (4) The universal moment generating function (UMGF) approach.

The total investment-cost minimization problem, subject to reliability constraints, is a well-known sequence

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ISSN 1335-3632

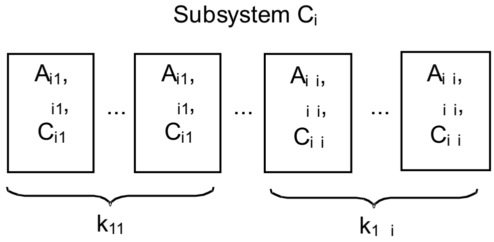

Fig. 2. Detailed structure of a given subsystem

of ROP. This problem has been studied in many different forms as summarized in (Tillman, Hwang and Kuo, 1997). The ROP for the multi-state reliability was introduced in (Ushakov, 1997). In (Levitin, 2000), genetic algorithms were used to find the optimal or nearly optimal system structure. This work uses an ACO to solve the new redesign problem. The idea of employing a colony of cooperating agents was recently proposed in (Dorigo, Maniezzo and Colorni, 1996). It has been successfully applied to the classical traveling salesman problem (Dorigo and Gambardella, 1997) and quadratic assignment problem (Maniezzo and Colorni, 1999). It has been recently adapted for the reliability design of binary state systems (Liang and Smith, 2001). The ant colony has also been adapted to other combinatorial problems such as management (Di Caro and Dorigo, 1998), graph coloring (Costa and Hertz, 1997) and constraint satisfaction (Schoofs and Naudts, 2000). The ACO has not yet been used for the new redesign problem.

The problem formulated above is a combinatorial optimization one. The ACO will be adapted to the problem. During the optimization process, artificial ants will have to evaluate the availability of a given selected structure. To do this, a fast procedure of availability estimation is developed. This procedure is based on a modern mathematical technique: the z-transform or universal moment generating (UMGF) function which was introduced in (Ushakov, 1986). The UMGF is an extension of the ordinary moment generating function (Ross, 1993).

The remainder of this paper is outlined as follows: In section 2, the new redesign problem is formulated. In section 3, availability evaluation method is developed. In section 4, the ant colony optimization method. In section 5, illustrative examples and numerical results are presented. Conclusions are drawn in section 6.

2 NEW REDESIGN PROBLEM

There has been much interest in power production models, where new redesign is considered. To formulate the new redesign problem, let consider a series-parallel power system containing n subsystems C_i $(i = 1, 2, \dots, n)$ in series as sketched in Fig. 1. Each component C_i in turn contains a number of different components connected in parallel. All components of any given subsystem belong to different version v. Components are characterized by their availability (A_{iv}), cost (C_{iv}) and performance (Ξ_{iv}) according to their version. The structure of subsystem i can be defined by the numbers of parallel components k_{iv} for $1 \le v \le V_i$, where V_i is the number of versions available for component of type i. Figure 2 illustrates these notations for a given component i. Each version k_{iv} contains m-identical components which are also connected in parallel. The entire system can therefore be defined by the set of triplets $\boldsymbol{k}_0 = \{A_{iv}, \Xi_{iv}, C_{iv}\}$ $(1 \le i \le n,\ 1 \le v \le V_i)$. Here $\boldsymbol{k}_0$ represents the initial system structure. In fact, for given triplet $\boldsymbol{k}_0$, the total cost of the power system structure can be calculated as

$$C = \sum_{i=1}^{n} \sum_{v=1}^{V_i} k_{iv} C_{iv} \,. \tag{1}$$

2.1 Initial optimal design

The multi-state design system problem of electrical power system at the initial period can be formulated as follows: find the minimal cost system configuration $\boldsymbol{k}_1, \boldsymbol{k}_2, \dots, \boldsymbol{k}_n$, such that the corresponding availability exceeds or equals the specified availability A_0. That is,

$$\text{Minimize} \qquad 1C = \sum_{i=1}^{n} \sum_{v=1}^{V_i} k_{iv} C_{iv} \tag{2}$$

$$\text{subject to} \qquad A(\boldsymbol{k}_1, \boldsymbol{k}_2, \dots, \boldsymbol{k}_n, \boldsymbol{D}, \boldsymbol{T}) \ge A_0 \tag{3}$$

2.2 The new redesign problem

In the cases when the production system is not able to satisfy the consumer demand, the existing system structure must be redesigned. This is the way to enhance system performance and/or improve reliability. This solution is more realistic, practical. Indeed, the system should be redesigned at different stages of the study period Y in which the load curve demand varies from stage to stage. Each stage θ begins $\tau(\theta)$ years after the initial stage (*ie*, initial stage 0). To provide the desired level of productivity and reliability, systematically the new components can be chosen from different versions of any given subsystem component. For each subsystem component i there are several component versions available in the market. A set of parameters contain the nominal capacity (Ξ_{ih}), availability (A_{ih}) and cost (C_{ih}) is specified for each version h of component of type i. Therefore, the component can be defined by $r_{ih}(\theta)$ $(1 \le h \le H_l)$ where H_l defines the total number versions of the redesigned system.

The entire redesign system may be defined by vectors $\boldsymbol{r}_i(\theta) = \{r_{ih}\}$ $(1 \le i \le n,\ 1 \le h \le H_l)$ at stage (θ). For a given set of $\boldsymbol{r}_1(\theta), \boldsymbol{r}_2(\theta), \dots, \boldsymbol{r}_n(\theta)$, the total cost of the system expansion at stage (θ) can be calculated as

$$C(\theta) = \frac{1}{(1+IP)^{\tau(\theta)}} \sum_{i=1}^{n} \sum_{h=1}^{H_l} r_{ih}(\theta) C_{ih} \tag{4}$$

where IP represents the interest rate.

For a given redesigned structure $\boldsymbol{k}$ defined by vectors $\boldsymbol{k} = \{r_1(\theta), r_2(\theta), \dots, r_n(\theta)\}$, the total cost investment during each study period can be calculated as follows:

$$C(k) = \sum_{\theta=1}^{Y} \frac{1}{(1+IP)^{\tau(\theta)}} \sum_{i=1}^{n} \sum_{h=1}^{H_l} r_{ih}(\theta) C_{ih} \,. \quad (5)$$

2.3 Optimal redesigned problem

The multi-state redesigned system can be formulated as follows: find the minimal cost of system structure $(\boldsymbol{k}_0, \boldsymbol{k}, \boldsymbol{D}(\theta), \boldsymbol{T}(\theta))$ that meets or exceeds the required availability A_0. That is,

$$\text{Minimize} \quad C(k) = \sum_{\theta=1}^{Y} \frac{1}{(1+IP)^{\tau(\theta)}} \sum_{i=1}^{n} \sum_{h=1}^{H_l} r_{ih}(\theta) C_{ih} \quad (6)$$

$$\text{subject to} \qquad A\big(\boldsymbol{k}_0, \boldsymbol{k}, \boldsymbol{D}(\theta), \boldsymbol{T}(\theta)\big) \geq A_0 \quad (7)$$

To estimate the availability index at each stage of study, it is necessary to calculate the overall probability that the load demand corresponding to this stage is not met. This method refers to the availability of reparable multi-state system that is developed in the next section.

2.4 Availability of reparable multi-state systems

The considered system is composed of a number of failure prone units. This system is considered to have a range of performance levels. An important MSS measure is related to the ability of the system to satisfy a given demand. When applied to electric power systems, reliability is considered as a measure of the ability of the system to meet the load demand (D). This definition of the reliability index is widely used for power systems: see *eg*, (Murchland, 1975) and (Levitin, Lisnianski, Ben-Haim and Elmakis, 1998). The Loss of Load Probability index (LOLP) is usually used to estimate the reliability index (Billinton and Allan, 1990). This index is the overall probability that the load demand will not be met. Thus, we can write $R = \text{Probab}(\Xi \geq D)$ or $R = 1 - \text{LOLP}$ with $\text{LOLP} = \text{Probab}(\Xi < D)$. This reliability index depends on consumer demand D.

For reparable MSS, the steady-state availability E is used as $\text{Probab}(\Xi \geq D)$ after enough time has passed for this probability to become constant. In the steady-state the distribution of states probabilities is given by equation (8), while the multi-state stationary availability is formulated by equation (9):

$$P_j = \lim_{t\to\infty} \big[\text{Probab}\big(\Xi(t) = \Xi_j\big)\big] \quad (8)$$

$$E = \sum_{\Xi_j \geq D} P_j \quad (9)$$

At each operation period of stage (θ) the demand distribution cumulative curve is predicted. The period of stage (θ) is divided into M_θ intervals with durations $T_j(\theta)$ $(1 \leq j \leq M_\theta)$ and each interval has a required demand level $D_j(\theta)$. We denote by $\boldsymbol{D}(\theta)$ and $\boldsymbol{T}(\theta)$ the vectors $\{D_j(\theta)\}$ and $\{T_j(\theta)\}$ $(1 \leq j \leq M_\theta)$, respectively. Then the generalized MSS availability index A at each stage can be calculated as

$$A = \frac{1}{\sum_{j=1}^{M} T_j(\theta)} \sum_{j=1}^{M} \text{Probab}\big(\Xi_T(\theta) \geq D_j\big) T_j(\theta) \,. \quad (10)$$

3 MULTI–STATE SYSTEM AVAILABILITY ESTIMATION METHOD

The procedure used is based on the universal z-transform, which is a modern mathematical technique introduced in (Ushakov, 1986). This method, convenient for numerical implementation, is proved to be very effective for high dimension combinatorial problems. In the literature, the universal z-transform is also called UMGF or simply u-transform. The UMGF extends the widely known ordinary moment generating function (Ross, 1993). The UMGF of a discrete random variable Ξ is defined as a polynomial

$$u(z) = \sum_{j=1}^{J} P_j z^{\Xi_j} \quad (11)$$

where the variable Ξ has J possible values and P_j is the probability that Ξ is equal to Ξ_j.

The probabilistic characteristics of the random variable Ξ can be found using the function $u(z)$. In particular, if the discrete random variable Ξ is the MSS stationary output performance, the availability E is given by the probability $\text{Probab}(\Xi \geq D)$ which can be defined as follows:

$$\text{Probab}(\Xi \geq D) = \Psi\big(u(z) z^{-D}\big) \quad (12)$$

where Ψ is a distributive operator defined by expressions (13) and (14):

$$\Psi\big(P z^{\sigma - D}\big) = \begin{cases} P, & \text{if } \sigma \geq D\,, \\ 0, & \text{if } \sigma < D\,, \end{cases} \quad (13)$$

$$\Psi\Big(\sum_{j=1}^{J} P_j z^{\Xi_j - D}\Big) = \sum_{j=1}^{J} \Psi\big(P_j z^{\Xi_j - D}\big) \,. \quad (14)$$

It can be easily shown that equations (13)-(14) meet condition $\text{Probab}(\Xi \geq D) = \sum_{\Xi_j \geq D} P_j$. By using the operator Ψ, the coefficients of polynomial $u(z)$ are summed for every term with $\Xi_j \geq D$, and the probability that Ξ is not less than some arbitrary value D is systematically obtained.

Consider single components with total failures and each component i has nominal performance Ξ_i and availability A_i. The UMGF of such a component has only two terms and can be defined as:

$$u_i(z) = (1 - A_i) z^0 + A_i z^{\Xi_i} = (1 - A_i) + A_i z^{\Xi_i} \,. \quad (15)$$

To evaluate the MSS availability of a series- parallel system, two basic composition operators are introduced. These operators determine the polynomial u(z) for a group of components.

3.1. Parallel components

Let consider a system component m containing J_m components connected in parallel. The total performance of the parallel system is the sum of performances of all its components. In power systems, the term capacity is usually used to indicate the quantitative performance measure of a component (Chern, 1992). Examples: generating capacity for a generator, carrying capacity for an electric transmission line, *etc*. Therefore, the total performance of the parallel unit is the sum of performances (Ushakov, 1986). The u-function of MSS component m containing J_m parallel components can be calculated by using the Γ operator: $u_p(z) = \Gamma(u_1(z), u_2(z), \dots u_n(z))$ where $\Gamma(g_1, g_2, \dots, g_n) = \sum_{i=1}^n g_i$. Therefore for a pair of components connected in parallel: $\Gamma(u_1(z), u_2(z)) = \Gamma\Big(\sum_{i=1}^n P_i z^{a_i}, \sum_{j=1}^m Q_j z^{b_j}\Big) = \sum_{i=1}^n \sum_{j=1}^m P_i Q_j z^{a_i+b_j}$. The parameters a_i and b_j are physically interpreted as the performances of the two components. n and m are numbers of possible performance levels for these components. P_i and Q_j are steady-state probabilities of possible performance levels for components. One can see that the Γ operator is simply a product of the individual u-functions. Thus, the component UMGF is: $u_p(z) = \prod_{j=1}^{J_m} u_j(z)$. Given the individual UMGF of components defined in equation (15), we have: $u_p(z) = \prod_{j=1}^{J_m}(1 - A_j + A_j z^{\Xi_i})$.

3.2 Series components

When the components are connected in series, the component with the least performance becomes the bottleneck of the system. This component therefore defines the total system productivity. To calculate the u-function for a system containing n components connected in series, the operator η should be used: $u_s(z) = \eta(u_1(z), u_2(z), \dots, u_m(z))$ where $\eta(g_1, g_2, \dots, g_m) = \min\{g_1, g_2, \dots, g_m\}$ so that $\eta(u_1(z), u_2(z)) =$

$$= \eta\Big(\sum_{i=1}^n P_i z^{a_i}, \sum_{j=1}^m Q_j z^{b_j}\Big) = \sum_{i=1}^n \sum_{j=1}^m P_i Q_j z^{\min\{a_i, b_j\}}.$$

Applying composition operators Γ and η consecutively, one can obtain the UMGF of the entire series-parallel system. To do this we must first determine the individual UMGF of each component.

3.3 Components with total failures

Let us consider the usual case where only total failures are considered and each subsystem of type i and version v_i has nominal performance Ξ_{iv} and availability A_{iv}. In this case, we have: $\mathrm{Probab}(\Xi = \Xi_{iv}) = A_{iv}$ and $\mathrm{Probab}(\Xi = D) = 1 - A_{iv}$. The UMGF of such a component has only two terms and can be defined as in equation (11) by

$$u_i^*(z) = (1 - A_{iv})z^0 + A_{iv} z^{\Xi_{iv}} = 1 - A_{iv} + A_{iv} z^{\Xi_{iv}}.$$

Using the Γ operator, we can obtain the UMGF of the i-th system component containing k_i parallel components as $u_i(z) = \big(u_i^*(z)\big)^{k_i} = \big(A_{iv} z^{\Xi_{iv}} + (1 - A_{iv})\big)^{k_i}$. The UMGF of the entire system containing n components connected in series is:

$$u_s(z) = \eta\big((A_{1v} z^{\Xi_1} + (1 - A_{1v})^{k_1}, (A_{2v} z^{\Xi_{2v}} + (1 - A_{2v})^{k_2}, \dots, (A_{nv} z^{\Xi_{nv}} + (1 - A_{nv})^{k_n}\big) \quad (16)$$

To evaluate the probability $\mathrm{Probab}(\Xi \geq D)$ for the entire system, the operator Ψ is applied to equation (12):

$$\mathrm{Probab}(\Xi \geq D) = \Psi\big(u_s(z) z^{-D}\big). \quad (17)$$

4 THE ANT COLONY OPTIMIZATION

Ants lay down in some quantity an aromatic substance, known as pheromone, in their way to food. The pheromone quantity depends on the length of the path and quality of the discovered food source. An ant chooses a specific path in correlation with the intensity of the pheromone. The pheromone trail evaporates over time if no more pheromone is laid down. Other ants can observe the pheromone trail and are attached to follow it. Thus, the path will be marked again and will therefore attract more ants. The pheromone trail on paths leading to a rich food source close to the nest will be more frequented and will therefore grow faster. In that way, the best solution has more intensive pheromone and higher probability to be chosen. The described behavior of real ant colonies can be used to solve combinatorial problems by simulation: artificial ants searching for the solution simulate real ants searching their environment. The objective values correspond to the quality of the food sources. The ACO approach associates pheromone trails to features of the solutions of a combinatorial problem, which can be seen as a kind of adaptive memory of the previous solutions. In addition, the artificial ants are equipped with a local heuristic function to guide their search through the set of feasible solutions. The pheromone trails are updated after the construction of a solution, enforcing that the best features will have a more intensive pheromone.

The general algorithm

To apply the ACO meta-heuristic to a combinatorial optimization problem, it is convenient to represent the problem by a graph $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{S})$, where $\boldsymbol{N}$ are the nodes and $\boldsymbol{S}$ is the set of edges. To represent our ROP as such a graph, the set of nodes $\boldsymbol{N}$ is given by subsystem and components, and edges connect each subsystem to its available components. Some nodes are added to represent positions where an additional component was not used. As in (Liang and Smith, 2001), these nodes are called blank nodes and have attributes of zero. The obtained graph is partially connected. Ants cooperate by using

Table 1. Data examples

	Subsystems	Versions	Availability A	Cost C	Capacity Σ
1	Power Units	1	0.980	0.590	120
		2	0.977	0.535	100
		3	0.982	0.470	85
		4	0.978	0.420	85
2	HT Transformer	1	0.995	0.205	100
		2	0.996	0.189	92
		3	0.997	0.091	53
		4	0.997	0.056	28
		5	0.998	0.042	21
3	HT lines	1	0.971	7.525	100
		2	0.973	4.720	60
		3	0.971	3.590	40
		4	0.976	2.420	20
4	HT/MT Transformers	1	0.977	0.180	115
		2	0.978	0.160	100
		3	0.978	0.150	91
		4	0.983	0.121	72
		5	0.981	0.102	72
		6	0.971	0.096	72
5	MT Lines	1	0.984	7.525	100
		2	0.983	4.720	60
		3	0.987	3.590	40
		4	0.981	2.420	20

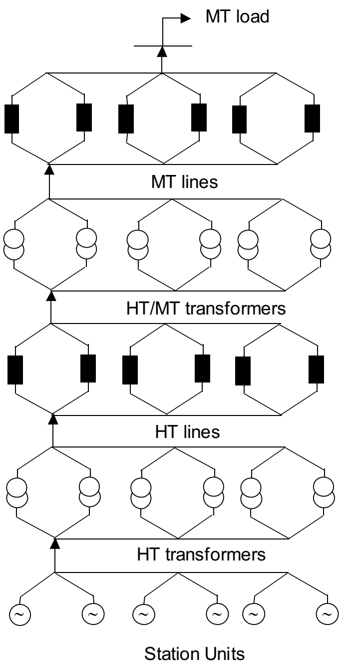

Fig. 3. Detailed electrical generating power station system

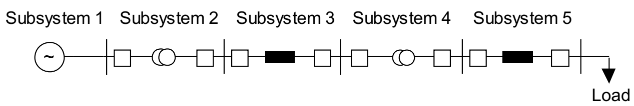

Fig. 4. Synoptic of the detailed electrical generating power station system

indirect form of communication mediated by pheromone they deposit on the edges of the graph $\boldsymbol{G}$ while building solutions.

In fact, the algorithm works as follows: N_b ants are initially positioned on a node representing a subsystem. Each ant looks for a solution and represents one possible configuration of the entire system. This configuration is represented by $\boldsymbol{K}_i$ components put in parallel for n different components. The $\boldsymbol{K}_i$ components can be chosen among any combination from $\boldsymbol{V}_i$ available types of components. Each ant builds a feasible solution (tour) to the expansion-planning problem. Applying this iteration becomes a stochastic rule. At each constructing solution, ant also modifies the amount of pheromone for each visited edges by a local updating rule. When all ants finished their tour, the pheromone amount is modified again by the global updating rule. Heuristic information (η_{ij})and pheromone amount (η_{ij}) guide the ants to build the best solution to select $\boldsymbol{K}_i$ components in each subsystem. At each node i an ant is positioned to choose the component j by applying the simple expression:

$$j = \begin{cases} \arg \max\limits_{m \in AC_i} \left([\tau_{im}]^{\alpha} [\eta_{im}]^{\beta} \right) & \text{if } q \le q_0 \,, \\ J & \text{Otherwise.} \end{cases} \tag{18}$$

and J is chosen according to the probability:

$$p_{ij} = \begin{cases} \frac{[\tau_{ij}]^{\alpha} [\eta_{ij}]^{\beta}}{\sum_{m \in AC_i} [\tau_{im}]^{\alpha} [\eta_{im}]^{\beta}} & \text{if } j \in AC_i \,, \\ 0 & \text{otherwise.} \end{cases} \tag{19}$$

where are: α - relative importance of the trail, β - relative importance of the heuristic information, η_{ij} AC_i - set of available components choices for subsystem i and q is random number uniformly generated between 0 and 1.

The heuristic information used is: $\eta_{ij} = 1/(1 + c_{ij})$ where c_{ij} represents the associated cost of component j for subsystem i. A "tuning" factor $t_i = \eta_{ij} = 1/(1 + c_{i(M_i+1)})$ is associated with blank component $(M_i + 1)$ of subsystem i. Parameter q_0 determines the relative importance of exploitation versus exploration: every time an ant in subsystem i has to choose a component j, it samples a random number $\le q \le 1$. If $q \le q_0$, then the best edge, according to (18), is chosen (exploitation), otherwise an edge is chosen according to (19).

The local updating pheromone

While the ants build a solution of the expansion-planning problem, these ants choose components by visiting the edges on the graph G, and their pheromone level is updated by the local rule given by:

$$\tau_{ij}^{new} = (1 - \rho) \tau_{ij}^{old} + \rho \tau_0 \tag{20}$$

where ρ is a coefficient such that $(1 - \rho)$ represents the evaporation of trail and τ_0 is an initial value of trail intensity. It is initialized to the value $(n \cdot TC_{nn})^{-1}$ with n being the size of the problem (*ie* number of subsystem and total number of available components) and TC_{nn} being the result of a solution obtained through some simple heuristic.

Table 3. Optimal solutions for new redesign problem

A_0	Structure	Stage0	Stage1=2 Years	Stage2=4 Years
0.975		Cost = 18.822	Cost = 18.771	Cost =20.967
	A	0.986	0.9825	0.9778
	Subsystem 1	1-2-3-4	1-3-3-4	1-2-3-4
	Subsystem 2	1-2-3-4-5	1-2-3-4-5	1-2-3-4-5
	Subsystem 3	2-3-4-4	2-3-4-4	1-4-4-4
	Subsystem 4	1-2-3-4-5-6	1-2-3-4-5-6	1-2-3-4-5-6
	Subsystem 5	2-3-4-4	2-3-3-4	1-2-3-4
0.985		Cost = 20.199	Cost = 20.199	Cost =24.267
	A	0.998	0.9953	0.985
	Subsystem 1	1-3-3-4	2-3-4-4	2-3-4-4
	Subsystem 2	1-2-3-4-5	1-3-4-4-5	1-2-3-4-5
	Subsystem 3	2-3-4-4	2-3-3-4	1-2-3-4
	Subsystem 4	1-2-3-4-5-6	1-2-3-4-5-6	1-2-3-4-5-6
	Subsystem 5	1-2-3-4	1-2-3-4	1-2-3-4

The global updating pheromone

After all ants have built a complete configuration, pheromone is updated only for the best ant. The amount of pheromone $\Delta\tau_{ij}$ is deposited on each edge that the best ant has used. This amount is given by $\frac{1}{TC_{best}}$ where TC_{best} is the total cost of the design. Therefore, the global updating pheromone can be given as

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\Delta\tau_{ij}\,, \tag{21}$$

$$\Delta\tau_{ij} = \begin{cases} \frac{1}{TC_{best}} & \text{if } (i,j) \in best \quad tour, \\ 0 & \text{otherwise.} \end{cases} \tag{22}$$

5 ILLUSTRATIVE EXAMPLE

5.1 Description of the system to be optimized

The electrical power station system which supplies the consumers is designed with five basic subsystems (stations) as depicted in Figs. 3 and 4. Figure 3 shows the detailed process of the electrical power station system distribution. The process of electrical power system distribution follows as: Electrical power is generated from the station units (subsystem 1). Then it is transformed to high voltage (HT) by the HT transformers (subsystem 2) and carried by the HT lines (subsystem 3). A second transformation occurs in HT/MT transformers (subsystem 4) which supply the MT load by the MT lines (subsystem 5). Each component of the system is considered as a unit with total failures. The characteristics of the products available on the market for each type of device are presented in Table 1. This table shown for each subsystem availability A, nominal capacity Σ and cost per unit C. Without loss of generality, both the component capacity and the demand levels can be measured as a percentage of the maximum capacity, Table 2.

Table 2. Parameters of cumulative load-demand curves

Stages #	Periods #		Different load curves			
1	0	D_i (%)	100	80	50	20
		T_i (h)	4203	788	1228	2536
2	2	D_i (%)	120	100	80	50
		T_i (h)	786	3065	2436	1572
3	4	D_i (%)	140	120	80	60
		T_i (h)	4203	788	1228	2536

Optimization result and discussion

For each study period a new redesign is obtained by the proposed ant algorithm for different values of A_0 (0.975 and 0.985). Table 3 illustrates the computed cost and availability index corresponding to their new design. In this experiment a set of value parameters of the ant algorithm are tested. The best values are: $\alpha = 5$, $\beta = 1$, $\tau_0 = 0.5$ and $\rho = 0.080$. The choice of these values affects strongly the solution.

To compare this met-heuristic to the combinatorial one, the space searching is about $50 * 450$ cycles, but in combinatorial one is 10^{48}.

The Program is running in PC Intel.4 for 1.6, GHz and the time to find the best solution is $3'.45''$. More than one day in the combinatorial method.

6 CONCLUSION

In this paper, we solve the new redesign problem which is a very interesting problem often reencounter in energy industry. It is formulated as a sequence of ROP as a new redesign at each study stage. The resolution of this problem uses a developing ACO method. This new algorithm for choosing an optimal series-parallel power structure configuration is proposed which minimizes the total investment cost subject to availability constraints. This algorithm seeks and selects components from among a list of available products according to their availability, nominal capacity (performance) and cost. Also defines the number and the kind of parallel components in each subsystem. The proposed method allows a practical way to solve wide instances of reliability optimization problem of multi-state power systems without limitation on the diversity of versions of components put in parallel. The combination used in this algorithm is based on the universal moment generating function and an ACO algorithm.

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Received 16 June 2003

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