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Electric Power Systems Research 76 (2005) 1–8

ELECTRIC POWER SYSTEMS RESEARCH

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Reliability optimization using ant colony algorithm under performance and cost constraints

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Received 18 May 2004; received in revised form 18 January 2005; accepted 1 February 2005

Abstract

Reliability engineers often try to achieve a high reliability level of production systems. The problem of electrical network reliability optimization where redundant electrical devices are included is considered. The system reliability maximization subject to performance and cost constraints is well known as reliability optimization problem. In reality, the system has a range of performance levels, in this case a multi-state system (MSS) reliability is defined as the ability to maintain a specified performance level. A procedure, which determines the maximal reliability of series–parallel electrical power system topology is proposed. In this procedure, electrical system devices are chosen among a list of available devices on the market. Electrical devices are characterized by their reliability, performance and cost. To evaluate the systems reliability, a universal moment generating function (UMGF) approach is used by the ant colony algorithm (ACA) to determine the optimal electrical power network topology.

A computer program has been developed to implement the UMGF technique combined with the ant colony algorithm. An illustrative example is treated at the end of this work.

Keywords: Reliability optimization; Multi-state system (MSS); Universal generating moment function (UMGF); Ant colony algorithm (ACA)

1. Introduction

This paper describes the use of an ant colony optimization to solve the allocation problem involving the selection of electrical devices and the appropriate levels of redundancy to maximize system reliability of series–parallel topology, under performance and cost constraints. A performing and reliable system for predefined missions under various constraints is very important in many industrial applications. The system redundancy, addressed in this paper is a common representation for many system design problems.

The devices allocation method discussed here is the selection of the optimal solution in the context of reliability optimization. Given the overall restrictions on the system performance, Ξ_0, and cost, C_0, the problem is to determine which topology to select and what kind of devices to use in order to achieve the maximum system reliability. This formulation of the redundancy allocation problem, such as that sketched in Fig. 1, leads to the maximization of system reliability of the series–parallel structure.

In this work, the objective is to adapt a new meta-heuristic ant colony algorithm (ACA), which includes a modern technique (Ushakov's technique) to select and evaluate the best configurations with maximal reliability under cost and performance constraints.

The remainder of this paper is organized as follows: in Section 2, the system reliability problem formulation is presented; in Section 3, the reliability estimation based on

Abbreviations: ACA, ant colony algorithm; MSS, multi-state system; ROP, redundancy optimization problem; UMGF, universal moment generating function

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doi:10.1016/j.epsr.2005.02.008

Ushakov's technique is developed; in Section 4, the ant algorithm is adapted to solve the system reliability optimization problem; in Section 5, illustrative examples and numerical results are presented; conclusions are drawn in Section 6.

2. System reliability problem

In the classical reliability, much work was devoted to the binary state reliability optimization analysis, where the system is either working perfectly or completely failed. Less effort has been expended to develop methods for analyzing and optimizing the reliability of multi-state systems (MSS). In this case, it is important to develop MSS reliability theory. In this paper, the system is considered to have a range of performance levels; MSS reliability theory will be used. The most of research works in MSS reliability can be found in [1,2]. Generally speaking, 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) technique.

Let consider a series–parallel electrical power system containing n subsystems $i = 1, 2, \ldots, n$ in series arrangement as represented in Fig. 1. Every subsystem i contains a number of different devices connected in parallel. For each subsystem i, there are a number of device versions available in the market. For each subsystem i, devices are characterized according to their version v by their performance (Ξ_{iv}), availability (A_{iv}) and cost (C_{iv}). The topology of subsystem i can be defined by the numbers of parallel devices (of each version) k_{iv} for $1 \leq v \leq V_i$, where V_i is the number of versions available for device of type i.

The entire system topology is defined by the vectors $k_i = \{k_{iv_i}\}$ $(1 \leq i \leq n, 1 \leq v \leq V_i)$. For a given set of vectors $k_1, k_2, \ldots, k_n$ the total cost of the system can be calculated as:

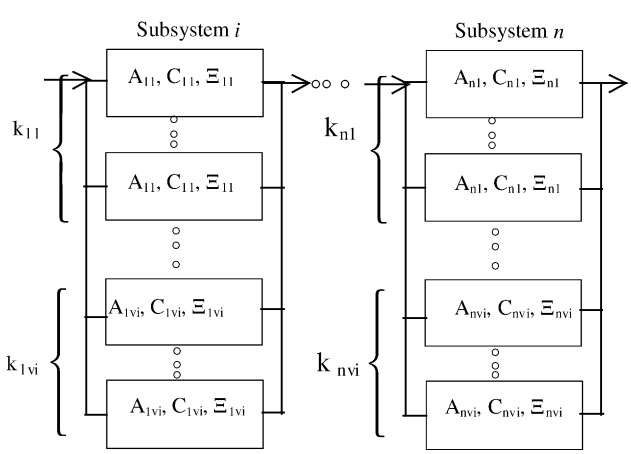

Fig. 1. Series–parallel power system topology.

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

The multi-state power system reliability optimization problem can be formulated as follows: find the topology corresponding to the maximal system reliability $k_1, k_2, \ldots, k_n$, such that the corresponding performance exceeds or equals the specified performance Ξ_0 and cost is less than the given cost C_0. That is,

Maximize

$$\begin{cases} \left\langle \sum_{i=1}^{n} \sum_{j=1}^{m} P_i Q_j z^{a_i + b_j} \right\rangle z^{-W} \\ \otimes \\ \left\langle \sum_{i=1}^{n} \sum_{j=1}^{m} P_i Q_j z^{\min\{a_i, b_j\}} \right\rangle z^{-W} \end{cases} \tag{2}$$

subject to

$$\begin{cases} \bullet \sum_{i=1}^{n} \sum_{v=1}^{V_i} k_{iv} C_{iv} \leq C_0 \\ \bullet\, \Xi^{\min\{a_i, b_j\}} \geq \Xi_0 \end{cases} \tag{3}$$

where a_i and b_j represent the performance of devices.

In electric power systems, reliability is considered as a measure of the ability of the system to meet the load demand (W), i.e., to provide an adequate supply of electrical energy (Ξ). This definition of the reliability index is widely used for power systems (see, e.g., [3,4]). The Loss of Load Probability index (LOLP) is usually used to estimate the reliability index in [5]. This index is the overall probability that the load demand will not be met. Thus, we can write $A = \text{Proba}(\Xi \geq W)$ and the $\text{LOLP} = 1 - A$. This reliability index depends on consumer demand W.

For reparable MSS, a multi-state steady-state availability E is used as $\text{Proba}(\Xi \geq W)$. In the steady-state, the distribution of states probabilities is given by Eq. (4), while the MSS stationary reliability is formulated by Eq. (5):

$$P_j = \lim_{t \to \infty} [\text{Proba}(\Xi(t) = \Xi)] \tag{4}$$

$$E = \sum_{\Xi_j \geq W} P_j \tag{5}$$

If the operation period T is divided into M intervals (with durations $T_1, T_2, \ldots, T_M$) and each interval has a required demand level ($W_1, W_2, \ldots, W_M$, respectively), then the generalized MSS reliability index A is:

$$A = \frac{1}{\sum_{j=1}^{M} T_j} \sum_{j=1}^{M} \text{Proba}(\Xi \geq W_j) T_j \tag{6}$$

We denote by $\boldsymbol{W}$ and $\boldsymbol{T}$ the vectors $\{W_j\}$ and $\{T_j\}$ $(1 \le j \le M)$, respectively. As the reliability A is a function of $k_1, k_2, \ldots, k_n$, $\boldsymbol{W}$ and $\boldsymbol{T}$. In the case of electrical power system, the vectors $\boldsymbol{W}$ and $\boldsymbol{T}$ define the cumulative load curve (consumer demand). In general, this curve is known for every power system. In [1], a comparison between these four approaches highlights that the UMGF technique is fast enough to be used in the complex problems where the search space is sizeable.

The problem of reliability maximization, subject to performance and cost constraints, is well known as the redundancy optimization problem (ROP). The ROP for series parallel systems is NP-hard [6] and has been studied in many different forms as summarized in [7], and more recently in [8]. The ROP for the MSS reliability was introduced in [9], where the general optimization approach was formulated. A modification of the gradient method was applied in [10] for finding the minimal cost topology of a series–parallel power system topology. Devices of the power system with different performances were considered, and the demand was estimated using a load curve. In [11], genetic algorithms were used to find the optimal or nearly optimal power system topology.

3. Reliability estimation based on Ushakov's technique

The last few years have seen the appearance of a number of works presenting various methods of MSS quantitative reliability estimation [12,13]. The procedure used in this paper for MSS availability evaluation is based on the universal z-transform technique. This method was introduced in [10] and has proved to be very effective for reliability evaluation of different types of multi-state systems. 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 [3].

The UMGF of a discrete random variable Ξ is defined as a polynomial:

$$u(z) = \sum_{j=1}^{J} P_j z^{\Xi_j} \tag{7}$$

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 A is given by the probability $\text{Proba}(\Xi \ge W)$ which can be defined as follows:

$$\text{Proba}(\Xi \ge W) = \Phi(u(z)z^{-W}) \tag{8}$$

where Φ is the distributive operator defined by expressions (9) and (10):

$$\Phi(Pz^{\sigma - W}) = \begin{cases} P, & \text{if } \sigma \ge W \\ 0, & \text{if } \sigma < W \end{cases} \tag{9}$$

$$\Phi\left(\sum_{j=1}^{J} P_j z^{\Xi_j - W}\right) = \sum_{j=1}^{J} \Phi(P_j z^{\Xi_j - W}) \tag{10}$$

It can be easily shown that Eqs. (9) and (10) meet condition $\text{Proba}(\Xi \ge \boldsymbol{W}) = \sum_{\Xi_j \ge W} P_j$. By using the operator Φ, the coefficients of polynomial $u(z)$ are summed for every term with $\Xi_j \ge \boldsymbol{W}$, and the probability that Ξ is not less than some arbitrary value $\boldsymbol{W}$ is systematically obtained.

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

$$u_i(z) = (1 - A_i)z^0 + A_i z^{\Xi_i} = (1 - A_i) + A_i z^{\Xi_i} \tag{11}$$

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 devices.

3.1. Parallel devices

Let consider subsystem m containing n devices connected in parallel. The total performance of the parallel system is the *sum* of performances of all its devices. In power systems, the term capacity is usually used to indicate the quantitative performance measure of a device in [6]. 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 capacity (performances) in [10]. The u-function of MSS subsystem m containing n parallel devices can be calculated by using the $\Im$ operator:

$$u_m(z) = \Im(u_1(z), u_2(z), \ldots, u_n(z)),$$

where

$$\Im(\Xi_1, \Xi_2, \ldots, \Xi_n) = \sum_{i=1}^{n} \Xi_i.$$

Therefore, for a pair of devices connected in parallel:

$$\Im(u_1(z), u_2(z)) = \Im\left(\sum_{i=1}^{K_1} P_i z^{a_i}, \sum_{j=1}^{K_2} Q_j z^{b_j}\right) = \sum_{i=1}^{K_1}\sum_{j=1}^{K_2} P_i Q_j z^{a_i + b_j}$$

The parameters a_i and b_j are physically interpreted as the performances of the two devices. K_1 and K_2 are numbers of possible performance levels for these devices. P_i and Q_j are steady-state probabilities of possible performance levels for devices. One can see that the $\Im$ operator is simply a product of the individual u-functions. Thus, the device UMGF is: $u_p(z) = \prod_{j=1}^{J_m} u_j(z)$. Given the individual UMGF of devices defined in Eq. (11), we have: $u_p(z) = \prod_{j=1}^{J_m}(1 - A_j + A_j z^{\Xi_i})$.

3.2. Series devices

When the devices are connected in series, the device with the least performance becomes the bottleneck of the system. This device therefore defines the total system productivity. To calculate the u-function for system containing n devices connected in series, the operator δ should be used: $u_s(z) = \delta(u_1(z), u_2(z), \ldots, u_n(z))$, where $\delta(\Xi_1, \Xi_2, \ldots, \Xi_n) = \min\{\Xi_1, \Xi_2, \ldots, \Xi_n\}$ so that

$$\delta(u_1(z), u_2(z)) = \delta\left(\sum_{i=1}^{K_1} P_i z^{a_i}, \sum_{j=1}^{K_2} Q_j z^{b_j}\right) = \sum_{i=1}^{K_1}\sum_{j=1}^{K_2} P_i Q_j z^{\min\{a_i, b_j\}}$$

Applying composition operators $\Im$ and δ consecutively, one can obtain the UMGF of the entire series–parallel system. To do this, we must first determine the individual UMGF of each device.

3.3. Devices with total failures

Let 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: $\text{Proba}(\Xi = \Xi_{iv}) = A_{iv}$ and $\text{Proba}(\Xi = 0) = 1 - A_{iv}$. The UMGF of such a device has only two terms can be defined as in Eq. (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 $\Im$ operator, we can obtain the UMGF of the ith subsystem containing k_i identical parallel devices $u_i(z) = (u_i^*(z))^{k_i} = (A_{iv} z^{\Xi_{iv}} + (1 - A_{iv}))^{k_i}$.

The UMGF of the entire system containing n subsystems connected in series, where each subsystem may contain different devices is:

$$u_s(z) = \delta(\Im(u_{11}(z), \ldots, u_{1k_1}(z)), \Im(u_{i1}(z), \ldots, u_{ik_i}(z)), \ldots, \Im(u_{n1}(z), \ldots, u_{nk_n}(z))) \tag{12}$$

To evaluate the probability, $\text{Proba}(\Xi \geq W)$, for the entire system, the operator Φ is applied to Eq. (12):

$$\text{Proba}(\Xi \geq W) = \Phi(u_s(z) z^{-W}) \tag{13}$$

4. The ant colony algorithm implementation

This paper uses an ACA using Ushakov technique to solve the ROP for MSS. The idea of employing a ants of cooperating agents to solve combinatorial optimization problems was recently proposed in [14]. The ACA has been successfully applied to the classical traveling salesman problem in [15], to the quadratic assignment problem in [16] and to scheduling in [17,18]. Ant algorithm shows very good results in each applied area. It has been recently adapted for the reliability design of binary state systems in [19]. The ACA has also been adapted with success to other combinatorial optimization problems such as the vehicle routing problem in [20], telecommunication networks management in [21], graph coloring in [22], constraint satisfaction in [23] and Hamiltonian graphs in [24].

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 attracted to follow it. Thus, the path will be marked again and will therefore attract more ants. The pheromone trail on paths leading to 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 the solution space simulate real ants searching their environment. The objective values correspond to the quality of the food sources. The ACA 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.

4.1. The general algorithm

To apply the ACA 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 problem 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 additional component was not used. As in [19], these nodes are called blanks nodes and have attributes of zero. The obtained graph is partially connected. Ants cooperate by using 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: Nb ants are initially positioned on nodes representing subsystems; each ant looks for a solution and represents one possible topology of the entire system. This topology is represented by $\boldsymbol{K}_i$ devices put in parallel for n different components. The $\boldsymbol{K}_i$ devices can be chosen among any combination from $\boldsymbol{V}_i$ available type of components. Each ant builds a feasible solution (tour) to the reliability optimization problem. Applying this iteration, become a stochastic rule. While constructing a solution, each ant also modifies the amount of pheromone for each visited edges by local updating rule. When all ants have finished their tour, the pheromone amount is modified again by global updating rule. An heuristic information (η_{ij}) and pheromone amount (τ_{ij}) guide the ants to built the best solution to select $\boldsymbol{K}_i$ optimal or near optimal devices in each subsystem. At each node i an ant is positioned to choose the device j by applying the simple expression:

$$j = \begin{cases} \arg \max\limits_{m \in AC_i} ([\tau_{im}]^{\alpha}[\eta_{im}]^{\beta}), & \text{if } q \leq q_0 \\ J, & \text{otherwise} \end{cases} \tag{14}$$

and J is chosen according to the probability:

$$p_{ij} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{m \in \mathrm{AC}_i}[\tau_{im}]^{\alpha}[\eta_{im}]^{\beta}}, & \text{if } j \in \mathrm{AC}_i \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

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

The heuristic information used is: $\eta_{ij} = 1/(1 + A_{ij})$, where A_{ij} represents the associated availability of device j for subsystem i. A "tuning" factor $t_i = \eta_{ij} = 1/(1 + A_i)$ is associated to blank device ($M_i + 1$) of subsystem i. The devices are arranged from the best reliable one to the worst reliable one. The parameter q_0 determines the relative importance of exploitation versus exploration: every time an ant in subsystem i have to choose a device j, it samples a random number $0 \leq q \leq 1$. If $q \leq q_0$ then the best edge, according to (14), is chosen (exploitation), otherwise an edge is chosen according to (15) (exploration).

4.2. The local updating pheromone

While the ants built a solution of the reliability optimization problem, these ants choose reliable device by visiting edges on the graph $\boldsymbol{G}$, and their pheromone level is updated by local rule given by:

$$\tau_{ij}^{\text{new}} = (1 - \rho)\tau_{ij}^{\text{old}} + \rho\tau_0 \tag{16}$$

where ρ is the 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 $(n\sum_{i=1}^{n} A_i)^{-1}$ (exploration) with n being the size of the problem (i.e., total number of available devices) and A_j the availability of the ith device.

4.3. The global updating pheromone

After all ants have built a complete configuration, pheromone is updated, only for the best ant. An amount of pheromone $\Delta\tau_{ij}$ is deposited on each edge that the best ant has used. This amount is given by $(\mathrm{TA}_{\text{best}})^{-1}$, where $\mathrm{TA}_{\text{-best}}$ is the system reliability of the best structure design determined in current cycle. Therefore, the global updating pheromone can be given as:

$$\tau_{ij}^{\text{new}} = (1 - \rho)\tau_{ij}^{\text{old}} + \rho\,\Delta\tau_{ij} \tag{17}$$

$$\Delta\tau_{ij} = \begin{cases} \dfrac{1}{\mathrm{TA}_{\text{nm best}}}, & \text{if } (i,\ j) \in \text{best tour} \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

4.4. Description of the ant algorithm

1. Initialization
   Repeat for each ant
   Repeat for each subsystem
2. Select a component
   /* This selection can return blank components; no real component selected */
3. Apply local updating to the selected component using Eqs. (14) and (15)
   repeat 2 and 3 k_i times
   /* K_i: maximum number of components that can be placed in current subsystem i */
   until last subsystem
   compute structure cost, performance and availability
   until last ant
   evaluate and rank all ants in the colony
   apply global updating to the optimal structure in the current cycle using Eq. (16) and record this configuration

end of cycle
return to 1 for running new cycle
terminate ACA after Nc cycles
print optimal results.

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 as depicted in Fig. 2. The electrical power system can be described as follows: the electrical power is generated from the station units (subsystem 1). Then, transformed for 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 supplies the MT load through the MT lines (subsystem 5). Each device of the system is considered as 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 shows for each device availability, A, nominal performance, Ξ, and cost per unit, C. Table 2 shows the power demand levels and their corresponding durations. The power system structure should

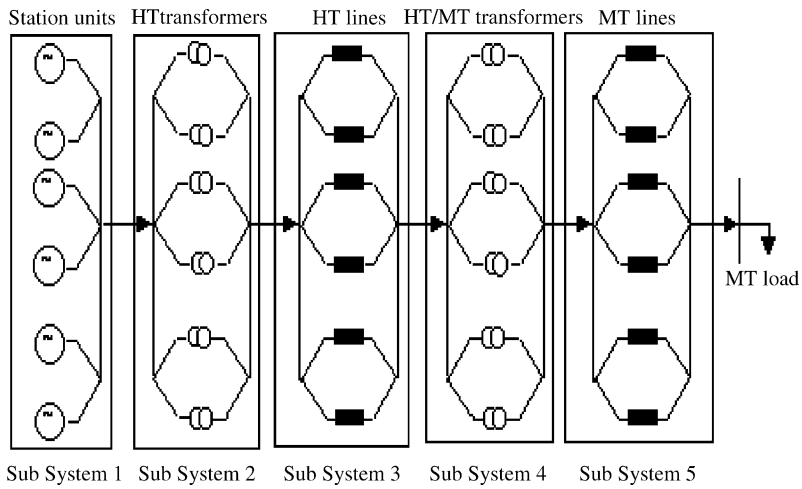

Fig. 2. Detailed electrical power system.

Table 1
Data examples

Sub no.	Dev no.	Avai, *A*	Cost, *C* (million US$)	Per Ξ (MW)
1. Power units	1	0.992	7.735	160
	2	0.986	6.475	140
	3	0.994	6.698	130
	4	0.988	6.290	120
	5	0.980	6.146	120
	6	0.991	4.484	90
	7	0.992	3.926	80
2. HT transformers	1	0.994	2.805	180
	2	0.990	2.772	180
	3	0.997	2.594	120
	4	0.991	2.569	120
	5	0.998	1.857	80
3. HT lines	1	0.971	1.985	160
	2	0.997	1.983	140
	3	0.991	1.842	140
	4	0.976	1.318	120
4. HT/MT transformers	1	0.978	0.842	160
	2	0.986	0.875	160
	3	0.978	0.745	140
	4	0.983	0.654	120
	5	0.981	0.625	120
	6	0.971	0.608	120
	7	0.985	0.492	100
	8	0.973	0.415	100
5. MT lines	1	0.984	0.456	140
	2	0.993	0.432	120
	3	0.989	0.364	100
	4	0.981	0.283	80
	5	0.968	0.242	80

Abbreviations: Sub, subsystems number; Dev, devices number; Avai, availability; Per Ξ, performance.

Table 2
Parameters of cumulative load–demand curve

Load (MW)	Duration (h)
720	1752
615	1752
540	3504
470	1752

be designed from available components and be able to meet the demand requirements at all load levels.

5.2. Discussion of obtained results

Table 3 illustrates the structures of the optimal or near optimal system configurations, which have the best availability levels and satisfy the cost and performance constraints. The system is designed by a combination of components selected from available versions shown in Table 1. Three optimal structures corresponding to different constraints are presented in this table. It can be seen for instance that for a desired performance of 820 MW and a cost constraint equal to US$ 82 million, the optimal structure provides an availability of 0.996. For the same performance and a cost constraint of US$ 75 million, the optimal configuration can only provide an availability of 0.989. Keeping the cost constraint at US$ 75 million and reducing the desired performance to 740 MW the availability of the System goes up optimally to 0.993.

Table 3 shows that no possible structure can be found that satisfies the performance level of 740 MW with a total cost constraint not exceeding US$ 62 million.

The algorithm proposed in this paper allows an evaluation of the tradeoff dependence between cost and performance on one hand, and system availability on the other hand.

The efficiency of this algorithm depends on the parameters selection and the trail update method.

Table 3
Optimal solutions for reliability optimization problem

Constraints		Topology	Optimal topology	Cost, reliability and performance		
C_0 (million US$)	Ξ_0 (MW)			C (million US$)	A (%)	Ξ (MW)
82	820	Subsystem 1	1–1–3–3–4–4–7	80.674	0.996	840
		Subsystem 2	1–1–1–1–3–5			
		Subsystem 3	2–2–2–2–3–3			
		Subsystem 4	2–2–2–4–7–7–7			
		Subsystem 5	2–2–2–2–2–3–3–3			
75	820	Subsystem 1	1–1–3–3–4–4	74.357	0.989	820
		Subsystem 2	1–1–1–3–5–5			
		Subsystem 3	2–2–2–3–3–4			
		Subsystem 4	2–2–4–7–7–7–7			
		Subsystem 5	1–1–1–2–2–2–3			
75	740	Subsystem 1	3–3–3–3–3–7–7	73.75	0.995	780
		Subsystem 2	1–1–3–3–5–5			
		Subsystem 3	2–2–2–2–2–4			
		Subsystem 4	7–7–7–7–7–7–7–7			
		Subsystem 5	2–2–2–2–3–3–3			
62	740	Subsystem 1	No possible structure	–	–	–
		Subsystem 2				
		Subsystem 3				
		Subsystem 4				
		Subsystem 5				

A set of values of ant algorithm parameters have been tested. The parameters considered are those that affect directly the computation of the formulas used in the algorithm (α, β and ρ). We tested several values for each parameter, all the others being constant. The values tested were: $\alpha \in \{0, 0.5, 1, 2\}$, $\beta \in \{0.5, 1, 2, 5, 10, 20\}$ and $\rho \in \{0.3, 0.5, 0.6, 0.7, 0.9\}$. The values for these parameters that converge rapidly to optimal solutions were: $\alpha = 1$, $\beta = 2$ and $\rho = 0.6$.

The program realization of the algorithm was run on a PC Intel 4 with 1.6 GHz and the running time for each optimization case did not exceed 105 s.

6. Conclusion

This paper describes how to implement the ant colony algorithm for finding the optimal series–parallel multi-state power system configurations.

The algorithm using heuristic information, selects, among a wide range of components available in the market, suitable versions and allocates them to structures in order to achieve maximum system reliability under cost and performance constraints. The method used in this paper consists of a combination of the universal moment generating function and an ant colony algorithm.

The ant colony algorithm is a promising heuristic method for solving complex combinatorial problems. This optimization method provides optimal or near optimal solutions in a search space of 40 ants × 100 cycles (4000 solutions), whereas obtaining an exact solution by the combinatorial method is not realistic.

Appendix A

List of symbols

A_{iv}	availability of jth MSS devices
a_i, b_j	performance levels
C_0	specified cost constraint
C_{iv}	cost of jth MSS devices
Nb	ants number
P_j	steady-state probability of performance levels of ith device
Q_j	steady-state probability of performance levels of jth devices
W	demand level
z	dummy transform variable
Ξ_{iv}	performance of jth devices of version v
Ξ_0	specified performance level
$\Im$	operator for parallel devices
σ	operator for series devices

References

[1] I.A. Ushakov, G. Levitin, A. Lisnianski, Multi-state system reliability: from theory to practice, in: Proceedings of the Third International Conference on Mathematical Methods in Reliability, MMR 2002, Trondheim, Norway, 2002, pp. 635–638.

[2] G. Levitin, A. Lisnianski, A new approach to solving problems of multi-state system reliability optimization, Qual. Reliab. Eng. Int. 47 (2) (2001) 93–104.

[3] S.M. Ross, Introduction to Probability Models, Academic Press, 1993.

[4] B. Murchland, Fundamental concepts and relations for reliability analysis of multi-state systems, in: R. Barlow, J. Fussell, N. Singpurwalla (Eds.), Reliability and Fault Tree Analysis, SIAM, Philadelphia, 1975.
[5] R. Billinton, R. Allan, Reliability Evaluation of Power Systems, Pitman, 1990.
[6] M.S. Chern, On the computational complexity of reliability redundancy allocation in a series system, Oper. Res. Lett. 11 (1992) 309–315.
[7] F. Tillman, C. Hwang, W. Kuo, Optimization techniques for system reliability with redundancy—a review, IEEE Trans. Reliab. R-26 (3) (1997) 148–155.
[8] C. Kuo, Prasad, An annotated overview of system-reliability optimization, IEEE Trans. Reliab. 49 (2) (2000) 176–187.
[9] I.A. Ushakov, Optimal standby problems and a universal generating function, Sov. J. Comput. Syst. Sci. 25 (4) (1987) 79–82.
[10] I.A. Ushakov, Universal generating function, Sov. J. Comput. Syst. Sci. 24 (5) (1986) 118–129.
[11] A. Lisnianski, G. Levitin, H. Ben-Haim, D. Elmakis, Power system structure optimization subject to reliability constraints, Electric Power Syst. Res. 39 (2) (1996) 145–152.
[12] B. Reinschki, System of Elements with Many States, Radio i svyaz, Moscow, 1985.
[13] E. EL-Neweihi, F. Proschan, Degradable systems: a survey of multi states system theory, Common Statis. Theory Math. 13 (4) (1984).
[14] M. Dorigo, V. Maniezzo, A. Colorni, The ant system: optimization by a colony of cooperating agents, IEEE Trans. Syst. Man Cybernet. Part B 26 (1) (1996) 1–13.
[15] M. Dorigo, L.M. Gambardella, Ant colony system: a cooperative learning approach to the traveling salesman problem, IEEE Trans. Evol. Comput. 1 (1) (1997) 53–66.
[16] V. Maniezzo, A. Colorni, The ant system applied to the quadratic assignment problem, IEEE Trans. Knowl. Data Eng. 11 (5) (1999) 769–778.
[17] A. Bauer, B. Bullnheimer, R.F. Hartl, C. Strauss, Minimizing total tardiness on a single machine using ant colony optimization, Central Eur. J. Operat. Res. 8 (2) (2000) 125–141.
[18] M. Den Besten, T. Stützle, M. Dorigo, Ant colony optimization fort he total weighted tardiness problem, in: Proceeding of the 6th International Conference on Parallel Problem Solving from Nature (PPSNVI), LNCS 2000, Berlin, 2000, pp. 611–620.
[19] Y.C. Liang, A.E. Smith, An ant colony optimization algorithm for the redundancy allocation problem (RAP), IEEE Trans. Reliab. 53 (3) (2004) 417–423.
[20] B. Bullnheimer, R.F. Hartl, C. Strauss, Applying the ant system to the vehicle routing problem, in: Second Metaheuristics International Conference (MIC-97), Sophia-Antipolis, France, 1997, pp. 21–24.
[21] G. Di Caro, M. Dorigo, Mobile agents for adaptive routing, in: Proceedings for the 31st Hawaii International Conference on System Sciences, Big Island of Hawaii, 1998, pp. 74–83.
[22] D. Costa, A. Hertz, Ants colour graphs, J. Operat. Res. Soc. 48 (1997) 295–305.
[23] L. Schoofs, B. Naudts, Ant colonies are good at solving contraint satisfaction problem, in: Proceeding of the 2000 Congress on Evolutionary Computation, San Diego, CA, July 2000, pp. 1190–1195.
[24] A. Wagner, A.M. Bruckstein, Hamiltonian(t)—an ant inspired heuristic for recognizing hamiltonian graphs, in: Proceeding of the 1999 Congress on Evolutionary Computation, Washington, DC, 1999, pp. 1465–1469.