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Efficient Artificial Immune Algorithm for Preventive-Maintenance-Planning For Multi State Systems

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Abstract

In this paper we use an artificial immune optimization algorithm in conjunction with the universal generating function (UGF) to solve the preventive maintenance (PM) problem for multi-state series-parallel system. In this work, we consider the situation where system and its components have several ranges of performance levels. Such systems are called multi-state systems (MSS). To enhance system availability or (reliability), scheduled preventive maintenance actions are performed to equipments. These PM actions affect strongly the effective age of components and increase system reliability. The MSS measure is related to the ability of the system to satisfy the demand. The objective is to develop an algorithm to generate an optimal sequence of maintenance actions for providing a system working with the desired level of availability or (reliability) during its lifetime with minimal maintenance cost. To evaluate the MSS system availability, a fast method based on UGF is suggested. The immune algorithm (IA) approach is applied as an optimization technique and adapted to this PM optimization problem.

Keywords: Universal generating function, Immune algorithm, Optimization, Preventive Maintenance.

Nomenclature:

C_{Mj} : Minimimal repair cost.

A_{iv} : Availability of j-th MSS devices.

h_j : Hazard function.

Q_j : Probability of failure of j-th devices.

Ξ_{iv}: Performance of j-th devices of version v.

W : Demand levels.

$\mathfrak{I}$: Distributive operator.

δ : operator for parallel devices.

Abbreviations:

IA : Immune Algorithm.

PM : Preventive maintenance.

MSS : Multi states system.

UMGF: Universal moment generating function.

I. INTRODUCTION

A necessary precondition for high production is availability of the technical equipment. In addition, reliability engineers have to build a reliable and efficient production system. The system reliability is affected essentially by the reliability of its equipments. This characteristic is a function of equipment age on system's operation life. In this work, we consider multi-states series-parallel systems. To keep the desired levels of availability, it is necessary to perform preventive maintenance actions to components rather than breakdown repairs. This suggestion is supported by a number of case studies demonstrating the benefits of PM in [1]. In this case, the task is to specify how PM activity should be scheduled. One of the commonly used PM policies is called *periodic* PM, which specifies that systems are maintained at integer multiple of some fixed period. Another PM is called *sequential* PM, in which the system is maintained at a sequence of interval that have unequal lengths. The first kind of PM is more convenient to schedule. Contrary the second is more realistic when the system requires more frequent maintenance in relation to equipment's age. A common assumption used in both these PM is that minimal repair is conducted on system if it fails between successive PM activities. In other words, minimal repairs do not change the hazard function or the effective age of the system.

Traditionally PM models assume that the system after PM is either as good as new state in this case it is called *perfect* PM or replacement, or as bad as old state which is equivalent to minimal repair, where only the function of the system is restored without affecting the system age [2]. However, the more realistic assumption is that the system after PM does not return to zero age and remains between as good as new and as bad as old. This kind of PM is called *imperfect* PM. The case when equipment fails, a corrective maintenance (CM) is performed which returns equipment to operating condition without reducing system age. in fact, the task of preventive maintenance actions served to adjust the virtual age of equipment. Our particular interest under investigation is to present an artificial immune algorithm which determines the optimal intervals of PM actions to minimize maintenance-cost rate while achieving desired mission reliability.

1.1. Summuray of previous work

Several years ago, much work was reported on policy optimization of preliminary planned PM actions with minimal repair as in [3-4]. Most of these researches are based on two popular approaches to determine the optimal intervals for a PM sequence. The first is reliability-based method and the second is optimization method.

In the first one the PM is performed whenever the system availability or the hazard function of the system reaches a predetermined level and the optimal PM intervals will be selected. The second is finding the optimal intervals as a decision variable in the optimization problem.

Wang [5] and Nakagawa [6] have treated a series–parallel configuration as a single piece of equipment in order to reduce the complexity of planning a PM strategy for multiple components. Some studies have addressed this issue by focusing on each system component to determine an overall PM strategy [7;8].

Due to inherent complexity of solving preventive maintenance problems, good results are obtained when meta-heuristic algorithms are utilized to solve various aspects of the preventive maintenance model.

[9] Presents an algorithm to determine the optimal intervals based on the reliability models of the effective age reduction and hazard function. [10] Presents a genetic algorithm to determine a minimal cost plan of the selecting PM actions which provides the required levels of power system reliability. A list of possible PM actions available for each MSS, are used. Each PM action is associated with cost and reduction age coefficient of its implementation. Shalaby *et al* (2004) [11] use a combination of genetic algorithm and simulation to solve the optimization problem for preventive maintenance scheduling of multi-component and multi-state systems. Suresh and Kumarappan (2006) [12] develop an optimization model and use a combination of genetic algorithm with simulated annealing. The authors apply their method to determine the preventive maintenance schedule in a power system. Samrout *et al* (2006) [13] present an algorithm based on the combination of an ant colony algorithm and genetic algorithm to optimize a large-scale preventive maintenance problem. However, there is still much work needed for improvements in search methods to increase the efficacy of solving any specified preventive maintenance problem.

1.2. Approach and outlines

The proposed approach is based on the optimization method using artificial immune algorithm, which determines the sequence of PM actions to minimize the maintenance-cost subject to availability and minimum system performance constraints. The goal of the proposed approach is to know *when, where, to which* component and *what kind* of available PM actions among the set of available PM actions should be implemented. To evaluate the reliability and the effect of PM actions of series-parallel MSS, UGF method is applied. It's proved to be effective at solving problems of MSS *redundancy* and *maintenance* in [14-15-16].

The rest of this paper is outlined as follows. We start in section 2 with the general description of the preventive maintenance model. Next, we describe the optimization problem formulation in section 3. A description of availability estimation based on UGF method is presented in section 4. In section 5, we present the artificial immune algorithm. Illustrative example and conclusion are given in section 6.

II. PREVENTIVE MAINTENANCE

It has been shown that the incorporation of the preventive maintenance has an economical benefit and the investment in PM not only pays for itself but also produces an important return on the investment. Also it was observed that the impact of the decrease of component failure rate and improvement of component reliability is vital to maintain efficiency of production. The major subject of maintenance is focused on the planning of the system maintenance service. However, all actions of PM not capable to reduce age component to zero age are imperfect. There are two main alternatives for modeling an imperfect PM activity. The first one assumes that PM is equivalent to minimal repair with probability p and $1-p$ is the equivalent to replacement in [17]. The second model directly analyzes how the hazard function or the effective age change after PM as in [9]. The proposed model is based on reduction age concept. Let consider the series-parallel MSS system shown in figures 1.

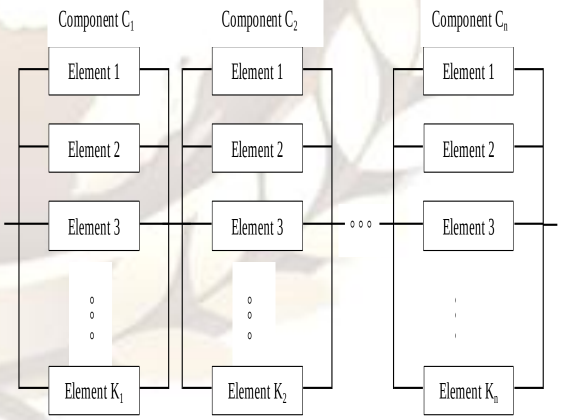

FIGURE.1. SERIES-PARALLEL POWER SYSTEM

If the component j undergoes PM actions at chronological calendar as follows:

$$(t_{j1},\ \ldots,\ t_{jn}) \tag{1}$$

Based on the second model description, the effective age after *i*-th PM actions may be written as:

$$\tau_j(t) = \tau_j^+(t) + (t - t_{ji}) \quad \text{for } t_{ji} < t < t_{ji+1}, (1 \le i \le n) \tag{2}$$

and $\tau_j^+(t_{ji}) = \varepsilon_i \tau_j(t_{ji}) = \varepsilon_i \left(\tau_j^+(t_{ji-1}) + (t_{ji} - t_{ji-1})\right)$

where $\tau_j^+(t_{ji})$ is the age of component immediately after the i–th PM action which ranges in the interval [0, 1]. By definition, we assume that $\tau_j(0) = 0$, $t_{j0} = 0$ and ε_i is the age reduction coefficient. Two limits for PM actions can be distinguished when $\varepsilon_i = 1$ and $\varepsilon_i = 0$. In the first case the component is only restored to "as bad as old" state which assumes that PM does not affect the effective age. In the second case the model reduce the component age to "as good as new", which means that the component age reaches zero age (replacement). In fact, all PM actions which improve the component age are imperfect. As it is mentioned and demonstrated in [9], the hazard function of component j, as function of its actual age, can be calculated as

$$h_j^* = h_j(\tau_j(t)) + h_{j0} \tag{3}$$

where $h_j(t)$ is the hazard function is defined when equipment does not undergo PM actions and h_{j0} correspond to the initial age of equipment. The reliability of the equipment j in the interval between PM actions i and $i+1$ can be written as:

$$r_j(t) = \exp\left(-\int_{\tau_j^+(t_{ji})}^{\tau_j(t)} h_j^*(x)dx\right) = \exp\left(H_j(\tau_j^+(t_{ji})) - H_j(\tau_j(t))\right) \tag{4}$$

$H_j(\tau)$ represents the accumulative hazard function. Clearly if $t = t_{ji}$ in equation (4) the reliability reaches the maximum and is equal to 1.

The Minimal repairs are performed if MSS equipment fails between PM actions, and there cost expected in interval [0, *t*] can be given as

$$C_{Mj} = c_j \int_0^t h_j(x)dx \tag{5}$$

Possible equipment j, undergoes PM actions at each chronological time $t_{j1}, \ldots, t_{jn_j}$, in this case, the total minimal repair cost is the sum of all cost can be written as :

$$C_{Mj} = c_j \sum_{i=0}^{n_j} \int_{\tau_j^+(t_{ji})}^{\tau_j(t_{ji+1})} h_j(x)dx = c_j \sum_{i=0}^{n_j} \left(H(\tau_j(t_{ji+1})) - H_j(\tau_j^+(t_{ji}))\right) \tag{6}$$

where $t_{j0} = 0$ and $t_{jn_j+1} = T$ where T represents the lifetime.

III. Optimization Problem

Let consider a power system organized with components connected in series arrangement. Each component contains different component put in parallel. Components are characterized by their nominal performance rate Ξ_j, hazard function $h_j(t)$ and associated minimal repair cost C_j. The system is composed of a number of failure prone components, such that the failure of some components leads only to a degradation of the system performance. This system is considered to have a range of performance levels from perfect working to complete failure. In fact, the system failure can lead to decreased capability to accomplish a given task, but not to complete failure. 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 (*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., [18-19-20-21-22]. The Loss of Load Probability index (LOLP) is usually used to estimate the reliability index [23]. This index is the overall probability that the load demand will not be met. Thus, we can write $R = Probab(\Xi_{MSS} \geq W)$ or $R = 1$-LOLP with LOLP = $Probab(\Xi_{MSS} < W)$. This reliability index depends on consumer demand *W*.

For reparable MSS, a multi-state steady-state instantaneous availability *A* is used as $Probab(\Xi_{MSS} \geq W)$. While the multi-state instantaneous availability is formulated by equation (7):

$$A_{MSS}\{t, W\} = \sum_{\Sigma_j \geq D} P_j(t) \tag{7}$$

where Ξ_{MSS} (t) is the output performance of MSS at time t. To keep system reliability at desired level, preventive and curative maintenance can be realized on each MSS. PM actions modify components reliability and CM actions does not affect it. The effectiveness of each PM actions is defined by the age reduction coefficient ε ranging from 0 to1. As in [10], the structure of the system as defined by an available list of possible PM actions (v) for a given MSS. In this list each PM actions (v) is associated with the cost of its implementation $C_p(v)$, and $M(v)$ is the number of equipment affected corresponding to their age reduction $\varepsilon(v)$. Commonly the system lifetime T is divided into y unequal lengths, and each interval have duration θ_y $1 \leq y \leq Y$, at each end of this latter an PM action is performed. This action will be performed if the MSS reliability $R(t, w)$ becomes lower than the desirable level R_0.

All the PM actions performed to maintain the MSS reliability are arranged and presented by a vector V as they appear on the PM list. Each time the PM is necessary to improve the system reliability; the following action to be performed is defined by the next number from this vector. When the scheduled PM action v_i was insufficient to improve reliability, automatically the v_{i+1} action should be performed at the same time and so on.

For a given vector V, the total number n_j and chronological times of PM action in equation (1) are determined for each component j $1 \le j \le J$. For all scheduled PM actions $v_i \in V$ the total cost of PM actions can be expressed as

$$C_p(V) = \sum_{i=1}^{N} C_p(v_i) \tag{8}$$

and the cost of minimal repair can be calculated as

$$C_M(V) = \sum_{j=1}^{J} c_j \sum_{i=0}^{n_j} \left(H(\tau_j(t_{ji+1})) - H(\tau_j^+(t_{ji})) \right) \tag{9}$$

The optimization problem can be formulated as follows: find the optimal sequence of the PM actions chosen from the list of available actions which minimizes the total maintenance cost while providing the desired MSS availability. That is,

Minimize:

$$f(V) \to C = C_p(V) + C_M(V) \tag{10}$$

Subject To:

$$A_\theta(\boldsymbol{V}, \boldsymbol{D}, \boldsymbol{t}) \ge R_0 \tag{11}$$

To solve this combinatorial optimization problem, it is important to have an effective and fast procedure to evaluate the availability index. Thus, a method is developed in the following section to estimate the system availability.

IV. Reliability Estimation Based On Ushakov's Method

The last few years have seen the appearance of a number of works presenting various methods of quantitative estimation of systems consisting of devices that have a range of working levels in [24-25]. Usually one considers reducible systems. In general forms the series connection, the level of working is determined by the worst state observed for any one of the devices, while for parallel connection is determined by the best state. However, such the approach is not applicable for the majority of real systems.

In this paper the procedure used is based on the universal *z*-transform, which is a modern mathematical technique introduced in [26]. 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 [11]. The UMGF of a discrete random variable Ξ is defined as a polynomial:

$$u(z) = \sum_{j=1}^{J} P_j z^{\Xi_j} \tag{12}$$

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:

$$\text{Proba}(\Xi \ge W) = \Phi\left(u(z)z^{-W}\right) \tag{13}$$

where Φ is a distributive operator defined by expressions (14) and (15):

$$\Phi(Pz^{\sigma - W}) = \begin{cases} P, & \text{if } \sigma \ge W \\ 0, & \text{if } \sigma < W \end{cases} \tag{14}$$

$$\Phi\left(\sum_{j=1}^{J} P_j z^{\Xi_j - W}\right) = \sum_{j=1}^{J} \Phi\left(P_j z^{\Xi_j - W}\right) \tag{15}$$

It can be easily shown that equations (14)–(15) meet condition *Proba*($\Xi \ge$ ***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 ***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 an device has only two terms can be defined as:

$$u_i(z) = (1 - A_i)z^0 + A_i z^{\Xi_i} = (1 - A_i) + A_i z^{\Xi_i} \tag{16}$$

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.

Parallel devices*:* Let consider a system device m containing J_m 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 [27]. 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 [26]. The *u*-function of MSS device m containing J_m parallel devices can be calculated by using the $\Im$ operator:

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

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

Therefore for a pair of devices connected in parallel:

$$\Im(u_1(z),\ u_2(z) = \Im(\sum_{i=1}^{n} P_i z^{a_i},\ \sum_{j=1}^{m} Q_j z^{b_j})$$

$$= \sum_{i=1}^{n}\sum_{j=1}^{m} P_i Q_j z^{a_i + b_j}$$

The parameters a_i and b_j are physically interpreted as the performances of the two devices. n and m 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 equation (11), we have: $u_p(z) = \prod_{j=1}^{J_m} (1 - A_j + A_j z^{\Xi_i})$.

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: $u_s(z) = \delta(u_1(z),\ u_2(z),\ \ldots,\ u_m(z))$, where $\delta(\Xi_1,\ \Xi_2,\ \ldots,\Xi_m) = \min\{\Xi_1,\ \Xi_2,\ \ldots,\ \Xi_m\}$ so that

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

$$= \sum_{i=1}^{n}\sum_{j=1}^{m} P_i Q_j z^{\min\{a_i,\ b_j\}}$$

Applying composition operators $\Im$ and δ consecutively, one can obtain the UMGF of the entire series-parallel system.

V. Artificial Immune System Optimization Algorithm

5.1 Immune system

The natural immune system is a powerful and efficient defence system that exhibits many signs of cognitive learning and intelligence [28]. In particular the acquired immune system, comprised mainly of lymphocytes which are special types of white blood cells, is a complex adaptive pattern-recognition system that defends the body from foreign pathogens (bacteria or viruses). The adaptive immune system uses lymphocytes, which can quickly evolve to destroy invading antigens. Lymphocytes exist in two forms, B cells and T cells. Each of this has distinct chemical structures and surface receptors molecules. The receptors' molecules attached primarily to the surface of B cells are called Antibodies whose aim is to recognize and bind to antigens (Jerne, 1973) [29].

When an antibody (Ab) strongly matches an invading antigen (Ag) the corresponding B-cell is selected to proliferate and start replicating itself. During this self-replicating process, a hyper mutation process takes place on the variable region of the B-cell. The hypermutation plays a critical role in creating diversity, increasing affinity and enhancing specificity of antibody. Figs. 3 and 4 [30,31] illustrate respectively the antigen recognition, the negative selection, clonal selection, expansion, and affinity maturation processes. A comprehensive survey of the IA theory, including the structure of its basic procedures, has been provided by N. de Castro and J. Von Zuben [30].

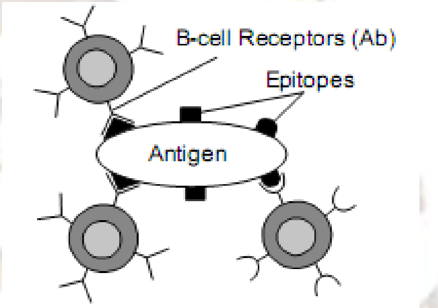

Fig 3: Recognition of an Antigen by a B-Cell Receptor.

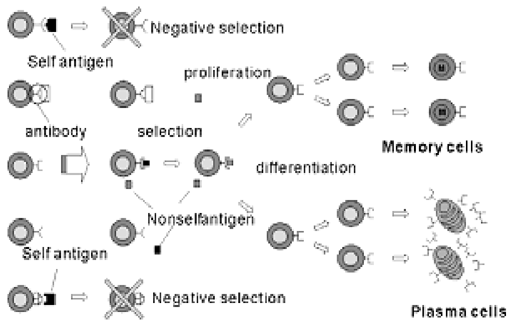

Fig 4: Negative and Clonal Selection Principle

5.2 Artificial Immune Systems

Artificial Immune Systems (AIS) are adaptive systems based on the emulation of the biological immune system behaviour and applied to problem solving. This new paradigm has already been identified as extremely useful in a wide range of engineering applications. The AIS, like genetic algorithms and neural nets, is an intelligent tool for advanced search procedures. (De Castro and Von Zuben, 2002a) [30]. In 1986 the theoretical immunologist, J.D. Farmer [32], first suggested a possible relationship between biological immunology and computing in a paper which compared natural immune systems, adaptation and machine learning. Since then, the field has expanded quickly, with numerous papers published by scientists applying AIS to a wide range of topics. Although algorithms based on the traits of AIS have been efficiently applied in various optimization tasks covering a wide range of real-world applications such as scheduling [33], buffer allocation problem BAP [34], and several other engineering applications [35 ;36 ;37 ;38], their application to Preventive maintenance problem has not been thoroughly explored. This work consists of a first time efficient application of an AIS algorithm based on the clonal selection paradigm in the PM problem for series-parallel multi-state systems under availability and performance constraint.

Encoding:

Every solution or antibody *Ab* is represented by a PM matrix $[PM]$.

$Ab = [PM]$

The matrix $[PM]$ has *N* columns and *L* lines, where:
L is the number of elements in the system and *N* the number of PM intervals. Each interval *i* has duration θ_i; $T = \sum_{i=1}^{N} \theta_i$; where T is system lifetime. Thus each line in the matrix represents the PM actions to be performed in sequence for the corresponding element.

$$\boldsymbol{Ab} = \begin{bmatrix} A_{11} & \cdots & A_{1n} \\ \vdots & \ddots & \vdots \\ A_{L1} & \cdots & A_{Ln} \end{bmatrix} \qquad (17)$$

Overview of the IA Algorithm

Step 1. Define antigen

The objective function that we aim to minimize and the availability constraint defined in eq. 7 represent the antigen. As illustrated in fig.4, the antigen represents the configuration of PM actions in the optimal solution of the optimization problem, and the corresponding segment of the antibody represents a trial solution for the variables. The antigen is recognised by the antibody receptors in a manner similar to a lock and a key relationship.

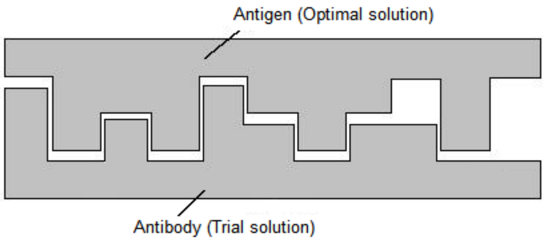

Fig 4. : Lock and Key Relationship between Antigen and Antibody

Step 2. Random initialization of antibody population

Initial integer-matrix antibody population is randomly generated. The antibody population represents PM actions vectors for each system component. As previously described, a position-based representation is used in this study to represent the antibody. This representation will generate valid offspring in the crossover and mutation procedures.

Step 3.

Evaluate fitness of antibodies to antigen

The fitness of each antibody to antigen in the population is calculated based on its objective function value and potential constraint violations. In evaluating the fitness of individual antibodies, constraint requirements were also examined. When a constraint is violated, the degree of violation is weighted to penalize the antibody's fitness. Antibodies with high fitness represent good individuals.

The fitness of each antibody is a positive number in the range $]0, \dots ,1[$ given by:

$$fit(\boldsymbol{Ab}^i) = \frac{1}{1 + cost_i + \omega[(R_0 - R_i) + |(R_0 - R_i)|]} \qquad (18)$$

Where:

$cost_i$ and R_i are respectively the cost and the availability of the configuration represented by antibody $(\boldsymbol{Ab}^i)$.

ω is a penalty factor used to penalize antibodies which violate the constraint requirement. In equation (20), the antigenic fitness of antibodies satisfying the availability constraint$(R_i \geq R_0)$ is a function of costs only.

STEP 4. Select *m* best antibodies to be kept in system memory (**M**).

Select the *n*, $(n \leq m)$ highest affinity antibodies in relation to the antigen for cloning.

STEP 5. Generate clone set (**C**)

Generate clone set (**C**) for the best n antibodies sorted in ascending order [$\boldsymbol{Ab}^i$ better individual than $\boldsymbol{Ab}^j$ for all (*j*>*i*)]. The number of copies is proportional to their affinities: the higher the affinity, the larger the clone size. The cloning of best n individuals is implemented by the rule:

$$NC_i = round\left(\frac{\lambda * n}{i}\right)$$

Where NC_i is the number of clones for antibody $\boldsymbol{Ab}^i$

n is the number of selected antibodies

λ is a size factor

For $n = 40$ and $\lambda = 1$, the highest affinity antibody (*i*=1) will produce 40 clones, while the second highest affinity (*i*=2) produces 20 clones, etc.

STEP 6. Execute genetic hypermutation and generate maturated clone set (**C***)

6.1 Mutation operations:

Cloned structures are mutated with a rate inversely proportional to their affinities with the antigen: the higher the affinity, the smaller the mutation rate. Mutation is executed following a biased probability rule that enables higher or lower mutation rates of antibodies according to their affinity with antigen as follows:
In each iteration *j*, and for each antibody *i*, evaluate the mutation threshold value as:

$$\eta = exp\{-\rho\, fit(Ab^i)\} \quad (19)$$

Generate a random number μ in interval [0, 1]

If $\mu \prec \eta$ then mutate antibody Ab^i, else move to next antibody.

6.2 Crossover operations:

The crossover operations are performed on the parents' vectors. To illustrate the crossover procedure let us consider a PM programme of six interventions and consider two parent antibodies Ab^1 and Ab^2. For illustration we only consider the PM vectors of the first element (first line in antibody matrix).

$$Ab^1 = \begin{bmatrix} 3 & 4 & 7 & 1 & 5 & 2 \\ \vdots & & \ddots & & & \vdots \\ A_{L1} & & \cdots & & & A_{L6} \end{bmatrix}$$

$$Ab^2 = \begin{bmatrix} 5 & \mathbf{2} & \mathbf{7} & \mathbf{3} & 1 & 6 \\ \vdots & & \ddots & & & \vdots \\ A_{L1} & & \cdots & & & A_{L6} \end{bmatrix}$$

To generate the first line of the offspring antibody Ab^{12} , we proceed as follows: the first line of antibody parent Ab^1 is copied in the offspring Ab^{12} then the fragment of genes between two arbitrary positions l and m of antibody parent Ab^2 $(1 \le l < m \le 6)$ are copied to the corresponding positions of offspring Ab^{12}. The crossover procedure for the first element (first line in antibody Ab^{12}) is illustrated for $l = 2$ *and* $m = 4$.

$$Ab^{12} = \begin{bmatrix} 3 & \mathbf{2} & \mathbf{7} & \mathbf{3} & 5 & 2 \\ \vdots & & \ddots & & & \vdots \\ A_{L1} & & \cdots & & & A_{L6} \end{bmatrix}$$

Crossover operations for the other components and the buffer vector are performed in a similar manner. For each component, the crossover procedure is executed only if the outcome of a randomly generated number ran $(0 \le ran \le 1)$ is less than a specified threshold limit TL. The value of the parameter TL can be set to depend on the cycle number. Equation (20) sets the threshold value for executing a crossover.

$$TL = exp\left(-\frac{T-G}{T}\right) - \beta \quad (20)$$

Where G is the evaluation number and T the maximal evaluation number and β a scaling factor. β was set to 0.2, so the crossover execution probability varies from 80% in the early stages of the optimization process to 17% in the late stages.

Place all antibodies issued of genetic operations in maturated clone set (**C***).

Step 7. Generate new random population (**R**).
Generate new random population (**R**) to replace the eliminated population in repertoire (**S**) and to avoid premature convergence to local optima.

Step 8: Place antibodies of (**C**), (**C***), (**M**), (**R**) in repertoire (**S**) and Survey newly generated antibodies

The antibody–antigen affinities $fit(Ab^i)$ of antibodies generated in Step 6 and 7 were evaluated. Moreover, to retain the antibody diversity in the current repertoire, affinity $Afin(Ab^i)$ (hereafter, "antibody-antibody affinity") between antibodies *i* and the best antibody in repertoire (P) were also investigated. Antibodies showing high affinity beyond a threshold limit *TL* with the best antibody are deleted with a deletion probability *P*(*d*) given by:

$$P(d) = \alpha^{\frac{G}{T}} \quad (21)$$

Where α is a probability scaling number in the range [0, 1], *G* the evaluation number and *T* the maximal evaluation number.
It is apparent from Eq. (21) that during early search stages antibodies having high "antibody antibody affinity" $Afin(Ab^i)$ are deleted with high probability allowing antibody diversity in the immune system memory and causing the search procedure to cover uniformly the decision space. At latter search stages when the space region likely containing the global optimum is located, near optimal individuals are allowed to perform fine local search.

The antibody-antibody affinity $Afin(Ab^i)$ in this study can be expressed as:

$$Afin(Ab^i) = \frac{1}{1+D_i} \quad (22)$$

$$D_i = \sum_{j=1}^{k-1} \delta_j$$

Where $$\delta_j = \begin{cases} 1 \ if \ (Ab^i)_j^k \neq (Ab^{best})_j^k \\ 0 \quad\quad otherwise \end{cases} \quad (23)$$

Where D_i is the Hamming distance between antibodies *i* and the best antibody, $(Ab^i)_j^k$ is the *jth* element in component *k* of antibody *i*, and $(Ab^{best})_j^k$ is the *jth* element in component *k* of the best antibody.
The Hamming distance between two antibodies is the number of equivalent locations for which the corresponding machines or buffers are different.

Step 10: Generate memory set (**M**) Reselect *m* highest affinity of these maturated individuals to be kept as memories of the immune system. Select *n* best affinity candidates for cloning.

Step 11: Repeat steps 6 to 10 until a certain stopping criterion is met. The stopping condition applied in this work is based on the stagnation feature of the algorithm (less than 0.1% change in the cost function in ten consecutive generations).

VI. Illustrative Example

Let consider a series-parallel MSS (Nuclear power systems) consisting of components connected in series arrangement as depicted in figure.3. The system contains 10 equipments with different performance and reliability, the process is done with basic components to transmit the stream energy to the electrical generator. The reliability of each component is defined by veibull function: $h(t) = \lambda^{\delta}\delta(\tau(t))^{\delta-1} + h_0$

MSS lifetime is 20 years. The time for possible PM_actions

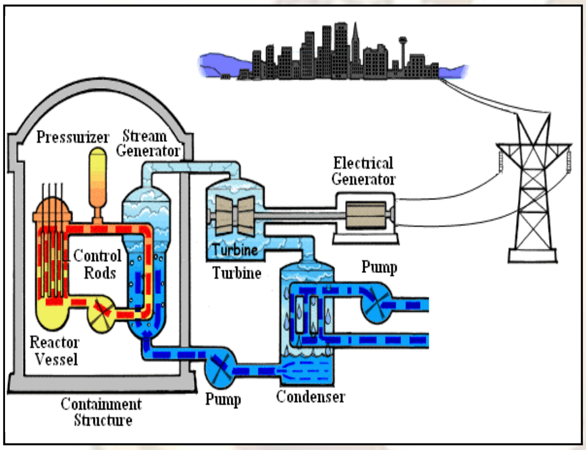

FIGURE.3. SERIES-PARALLEL NUCLEAR POWER SYSTEM

Are spaced by intervals of θ = 2 months. The problem is to find the best PM plan that achieves a system performance and reliability not less than (Ξ_0, R_0).

TABLE 1
PARAMETER OF ELEMENTS

	λ	δ	h_0	Min repair Cost	Ξ %
1	0.05	1.8	0.001	1.02	97
2	0.05	1.8	0.003	0.9	80
3	0.05	1.8	0.003	0.9	80
4	0.05	1.8	0.003	0.9	80
5	0.02	1.3	0.002	0.7	70
6	0.02	1.3	0.002	0.6	70
7	0.02	1.3	0.002	0.7	70
8	0.08	1.6	0.006	0.8	85
9	0.07	1.8	0.005	0.6	89
10	0.05	1.8	0.003	0.8	90

TABLE 2
PARAMETER OF PM_ACTIONS

PM_Action	Element Number	Age Reduction ε	PM_Cost 10^3 $
1	1	1	17.2
2	1	0.6	3.9
3	1	0.4	2.8
4	2	1	2.4
5	3	0.7	1.6
6	3	0.4	1.1
7	4	1	1.9
8	4	0.5	1.1
9	5	0.6	1.3
10	5	0.3	0.5
11	6	0.8	0.1
12	7	1	0.7
13	7	0.4	0.1
14	8	1	2.1
15	8	0.5	1.0
16	9	1	3.7
17	9	0.5	2.2
18	9	0.3	1.1
19	10	0.8	1.3

TABLE 3
THE BEST PM PLAN FOR R(T,0.85)>0.9

t	PM_Actions	Affected Elements	R (t,0.85)
02.250	8	4	0.907
05.652	13	7	0.912
07.120	20	10	0.917
09.312	5	3	0.922
11.648	17	9	0.934
14.046	12	7	0.939
16.343	4	2	0.931
17.879	8	4	0.914
19.671	2	1	0.918
Total PM Cost	13.9 10^3 $		

TABLE 4
THE BEST PM PLAN FOR R(T,0.85)>0.95

t	PM_Actions	Affected Elements	R (t,0.85)
01.783	8	4	0.952
03.547	13	7	0.959
06.054	19	10	0.966
08.131	5	3	0.956
09.894	18	9	0.951
11.576	4	2	0.959
13.077	12	7	0.964
14.634	7	4	0.954
15.714	17	9	0.957
17.237	2	1	0.965
18.368	8	4	0.955
19.749	20	10	0.951
Total PM Cost	18.2 10^3 $		

In this paper we formulated the problem of imperfect maintenance optimization for series-parallel nuclear power system structure. This work focused on selecting the optimal sequence of intervals to perform PM actions to improve the system reliability under system performance constraint. The model analyzes cost and reliability, to construct a strategy to select the optimal maintenance intervals, formulating a complex problem. We show results for two examples involving different reliability levels, to give an indication of how PM schedules can vary in response to changes in reliability of system. An exhaustive examination of all possible solution is not realistic, considering reasonable time limitations. Because of this, an efficient optimization algorithm based on artificial immune system was applied to solve the formulated problem. It can be seen from tables 3 and 4 for that more than more than 30% in PM spending is required to increase the power system reliability from 0.90 to 0.95 for desired minimum system performance not less than 85%.

To test the consistency of the proposed algorithm, the immune algorithm was repeated 50 times with different starting antibody repertoires and clone sizes. All immune procedures converged to the same values. The algorithm converged faster to optimal values when the antibody repertoire size and clone size parameters were set respectively to 250 and 30.

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