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An Artificial Immune System Based Solution for Generator Maintenance Scheduling

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ABSTRACT:*This paper presents a novel optimization approach to constrained generator maintenance scheduling (GMS) problem using artificial immune system (AIS). The approach utilizes the clonal selection principle wherein cloning of antibodies is performed followed by hypermutation. The proposed system, the artificial immune system has been formulated with respect to multiple objective and soft constraints. While genetic algorithm and other analytical methods might suffer from premature convergence and the curse of dimensionality, clonal algorithm can be efficient alternative. Clonal algorithm is known to effectively solve large scale multi-objective optimization problems. Simulations were performed on a system with large number of generating units and comparisons are performed with other prevalent approaches. The findings affirmed the robustness, fast convergence and proficiency of proposed methodology over other existingtechniques.*
KEY WARDS:*Artificial immune systems, clonal algorithm, maintenance scheduling, power systems.*

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I. INTRODUCTION

The economic operation of an electric utility system requires the simultaneous solution of all aspects of the operationschedulingprobleminthefaceofsystemcomplexity, different time-scales involved, uncertainties of different order, and dimensionality of problems. Utilities spend billions of dollars per year for maintenance. The reliability of system operation and production cost in an electric power system is affected by the maintenance outage of generating facilities. Optimized maintenance schedules could safe millions of dollars and potentially defer some capital expenditure for new plants in times of tightening reserve margins, and allow critical maintenance work to be performed which might not otherwise be done. Therefore, maintenance scheduling in the electric utility system is a significant part of the overall operations scheduling problem.

Power system components are made to remain in operating conditions by regular preventive maintenance. The task of generator maintenance is often performed manually by human experts who generate the schedule based on their experience and knowledge of the system, and in such cases there is no guarantee that the optimal or near optimal solution is found. Power system components are made to remain in operating conditions by regular preventive maintenance. The purpose of maintenance scheduling is to find the sequence of scheduled outages of generating units over a given period of time such that the level of energy reserve is maintained. This type of schedule is important mainly because other planning activities are directly affected by such decisions. In modern power systems the demand for electricity has greatly increased with related expansions in system size, which has resulted in higher number of generators and lower reserve margins making the generator maintenance scheduling **(**GMS) problem more complicated. The eventual aim of the GMS is the effective allocation of generating units for maintenance while maintaining high system reliability, reducing production cost, prolonging generator life time subject to some unit and system constraints [2, - 4].

The GMS is an optimization problem. Various methods exist in the literature that addresses optimization problems under different conditions. Different optimization techniques are classified based on the type of the search space and the objective function. The simplest method is linear programming (LP) which concerns the case where the objective function is linear [1, 6]. For a special case, wheresome or all variables are constrained to take on integer values, the technique is referred to as integer programming [1]. Even though deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters. This necessitates the introduction of dynamic programming (DP)

[9]. Although the DP technique has been mathematically proven to find an optimal solution, it has its own drawbacks. Solving the dynamic programming algorithm in most of the cases is not feasible and numerical solution requires extensive computational effort, which increases exponentially as the size of the problem increases.

The complexity is even further increased when moving from finite horizon to infinite horizon problems, while also considering the stochastic effects, model imperfectionsandthe presenceoftheexternaldisturbances[9]. Genetic algorithm (GA) can provide solution to GMS and the above optimization problems [5]. GA represents a particular class of evolutionary algorithms that uses techniques inspired by evolutionary biology such as inheritance, mutation, natural selection and crossover. While it can rapidly locate good solutions, it may have a tendency to converge towards local optimaratherthantheglobaloptimumoftheproblem[10]. In order to obtain approximate solution of a complex GMS, new concepts have emerged in recent years. They include applications of probabilistic approach [12], simulated annealing [13], decomposition technique [14] and genetic algorithm (GA) [15]. The application of GA to GMS presented in [10] have been compared with, and confirmed to be superior to other conventional algorithms such as heuristic approaches and branch-and-bound (B&B) in the quality of solutions. GMS using DE for the minimization of reliability cost function of levelling reserve generation over an entire period of 52 weeks maintenance window for the Nigerian power system have been reported in [16].

The natural immune system is a very complex system with several mechanisms for defense against pathogenic organisms. The main purpose of the immune system is to recognize all cells within the body and categorize those cells as either self or nonself. The immune system leans through evolution to distinguish between dangerous foreign antigens and the body's own cells or molecules. From an information-processing perspective, the immune system is a remarkable parallel and distributed adaptive system. It uses learning, memory and associative retrieval to solve recognition, classification and optimization tasks [8]. A few computational models have been developed based several principles of the immune system such as immune network model, negative selection algorithm, positive selection algorithm and clonal selection principle [I0].

The developed AIS Programme is used to determine the active power to be generated by the generating units in power generation systems, which are subjected to a number of inequality and equality constraints in older to achieve minimum generation cost while satisfying the load demand simultaneously. This paper presents a artificial immune system based for solution obtaining optimal generator maintenance scheduling for economical and reliable operation of a power system while satisfying system load demand and manpower constraints.

II. PROBLEMFORMULATION

Generator maintenance schedule is a preventive outage schedule for generating units in a power system within a specified time horizon. Maintenance scheduling becomes a complex optimization problem when the power system contains a number of generating units with different specifications,andwhennumerousconstraintshavetobetaken into consideration to obtain an optimal, practical and feasible solution. It is done for a time horizon of different durations. A planning horizon of one year (that is 52 weeks) for21generating units of different capacities is considered in the GMS problem presented in [2, 3]. The GMS over this planning period is important for resource management and future planning.

Generally, there are two main categories of objective functions in GMS, namely, based on reliability and economic cost [3]. This study applies the reliability criteria of leaving reserve generation for the entire period of study. This can be realized by minimizing the sum of squares of the reserve over theentireoperationalplanningperiod.Theproblemhasaseries of unit and system constraints to be satisfied. The constraints include thefollowing:

- Maintenance window and sequence constraints - defines the starting of maintenance at the beginning of an interval and finishes at the end of the same interval. The maintenance cannot be aborted or finished earlier thanscheduled.
- Crew and resource constraints - for each period, number of people to perform maintenance schedule cannot exceed the available crew. It defines manpower availability and the limits on the resources needed for maintenance activity at each timeperiod.
- Load and reliability constraints - total capacity of the units running at any interval should be not less than predicted load at that interval. The load demand on the power system is considered during the scheduling period.
- Spinning reserve - in order to maintain the electric power supply normally, there must be a spinning reserve to meet unexpected loaddemand.

Ti ⊂T is the set of periods when maintenance of unit i may start,

$T_i = \{t \in T: e_i \leq t \leq lp_i - d_i + 1\}$ for each i

We define,

$$X_{it} = \begin{cases} 1 \text{ if unit i starts maintenance} \\ \text{ in period t} \\ 0 \text{ otherwise} \end{cases}$$

to be the maintenance start indicator for unit i in period t.

Let S_{it} be the set of start time periods k such that if the maintenance of unit i starts at period k that unit will be in maintenance at period t, $S_{it} = \{k \in T_i: t - d_i + 1 \leq k \leq t\}$. Let it be the set of units which are allowed to be in maintenance in period t, $I_t = \{i: t \in T_t\}$. Then the problem can be formulated as a quadratic 0–1 programming problem as below.

The objective function is to minimization of the sum of squares of the reserve generation given by (1). In this paper, clonal algorithm (CA) is applied to minimize (1) subject to the constraints given by (2), (3) and (4).

$$\underset{X_{it}}{Min}\left\{\sum_t \left(\sum_i P_{it} - \sum_{i \in It} \sum_{K \in Sit} X_{ik} \cdot P_{ik} - L_t\right)^2\right\} \qquad (1)$$

subject to the maintenance window constraint

$$\sum_{t \in T_i} X_{it} = 1 \quad \forall_i \qquad (2)$$

the crew constraint

$$\sum_{i \in It} \sum_{K \in Sit} X_{ik} \cdot M_{ik} \leq AM_t \quad \forall_t \qquad (3)$$

and the load constraint

$$\sum_i P_{it} - \sum_{i \in It} \sum_{K \in Sit} X_{ik} \cdot P_{ik} \geq L_t \qquad (4)$$

the man power constraint is not as crisp as formulated in (3).

Let TMV be the total manpower violation, which is given by

$$\mathrm{TMV} = \sum_{t \in \mathrm{TMV}} \left(\sum_{i \in \mathrm{It}} \sum_{K \in \mathrm{Sit}} X_{ik}.M_{ik} - AM_t\right)$$

where

$$\mathrm{TMV} = \left(t: \sum_{i \in \mathrm{It}} \sum_{K \in \mathrm{Sit}} X_{ik}.M_{ik} > AM_t\right) \qquad (5)$$

For our test problem the reliability in the above formulation is quantified by the sum of squares of reserves (SSR). A solution with a high reliability (low SSR) but requiring some extra manpower (TMV > 0) may well be acceptable to a power utility as the unavailable manpower may be hired. Here we take account of this flexibility by assuming that extra manpower of about 5% of the total available man-weeks can be hired if this leads to better system reliability. An artificial immune system to find the best compromise between the values of SSR and TMV, using knowledge of typical trade-offs in maintenance schedules for the test problem.

III. REVIEW OF CLONALALGORITHM

The clonal selection principle is an algorithm used by the immune system to describe the basic features of an immune response to an antigenic stimulus. The main features of the clonal selection principle [7, 10].

- New cells are copies of their parents (done) subjected to a mutationmechanism.
- Elimination of newly differentiated lymphocytes carrying self-reacting receptors.
- Proliferation and differentiation on contact of mature cells with antigens
- The persistence of forbidden clones provides resistant to early elimination by self-antigens as the basis of autoimmune diseases.

The clonal selection algorithm reproduces those individuals with higher affinity and selects their improved matured off springs, where single members will be locally optimized and the newcomers yield a broader exploration of the search space. This characteristics makes the clonal selection algorithm is suitable for solving multi-modal Optimization problems.

The effect of varying the number of clones generatedaccording to the fitness (affinity) of the individual isinvestigated in this study. The flowchart for artificial immunesystem functioning is depicted in Figure 1.

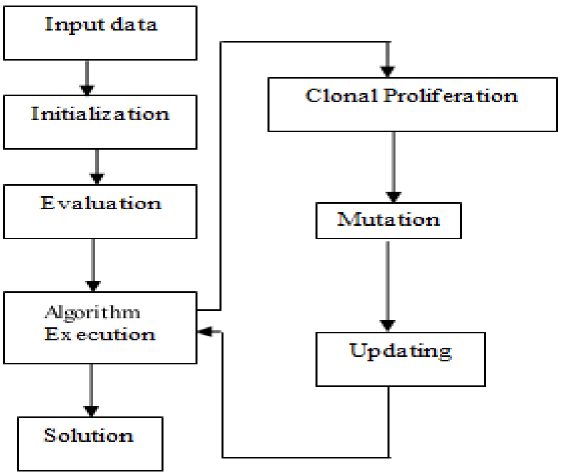

Figure 1. Flowchart for clonal algorithm

IV. IMPLEMENTATION OF CLONAL SELECTION TOGMS

The AIS is implemented to GMS problem utilizing four mainfeatures[10].Firstly, apoolofimmunecellsorantibodies isgenerated.Thisisfollowedbyproliferationwhichisactually cloning or copying of the parents. Then, maturation of these clones takes place which is analogous to hypermutation. Thereafter, the antibody–antigen interaction is evaluated followed by the elimination of self reacting immune cells or lymphocytes, i.e., individuals with low affinities or fitness values.

4.1. Encoding, initialization andcloning

Apopulationofantibodiesisinitializedusingbinarystrings each encoding a given solution to GMS problem. That is, the manpower maintenance from each of the generating unit is encoded into a binary form and a string is formed. This paper refers lymphocytes as the antibody and makes no distinction between a B-cell and its antibody. Each binary string is checked for constraint violation and penalized in case of infeasibility with penalty proportional to the extent of constraint violation. Affinity is calculated via fitness or objective values. Each of the antibodies from the initial pool is copied into a fixed number of clones to generate a temporary population of clones. This population of clones is made to undergo maturation process through hypermutation mechanism.Thehypermutationiscarriedoutviaaffinitybased hypermutation rate. Larger hypermutation rate is set for lower affinity clones and vice versa. That is, the probability of hypermutation of each clone is inversely to its affinity. This is followed by their affinity evaluation and penalty in case of any constraint violation. A new population of the same size as initial population of the antibodies is selected from themutated clones and this completes the first iteration. In the next iteration, this fresh population is made to undergo cloning and hypermutationasdiscussedaboveandlikewise[7].Thisarticle adopts robust AIS based strategy capable to solve GMS problem with reserve margin as well as manpower required comprising of a variety ofconstraints.

4.1.1. Parameter selection and algorithm details

The number of bits to encode a solution to the GMS problem is set as fifteen. The size of antibody population is assumed20andthenumberofclonesgeneratedperantibodyis kept dependent on its fitness value. The hypermutation is performed through stochastic genetic changes in which the probability of hypermutation is made dependent on the fitness of a clone. The algorithm starts with the random generation of binary strings which are then decoded into real values to check for constraint violation. In case of any constraint violation, the string is randomly generated again, decoded and checked for violation. This process is repeated iteratively until a deliberate fixed size of population isattained. When the population becomes full then each of the antibodies is evaluated and clones are generated. The number of clones generated per antibody is dependent in our solution methodologyontheaffinityorfitnessvalue,i.e.,largernumber of clones is generated for the antibodies with higher

fitness value.
The mutation rate is not taken uniform but kept inversely proportional to the fitness value of a given clone (binary flip mutation has been utilized with the probability of mutation varyingfrom0.035to0.010).Consequently,cloneswithhigher fitness are made liable to undergo mutation to a lesser extentas compared to those with lower fitness. Thereafter the mutated clones are decoded into their real values followed by the evaluation of corresponding affinity. This is repeated till allthe clones from the temporary clonal population are endured to mutation.Finally,tournamentselectionisdonetoselectsame number of mutated clones as there are in initial population. This completes one generation of the clonal selection algorithm. The convergence parameter is set as the situation when the best solutions of each generation cease to change. Thereby, stopping criteria is taken as convergence or the number of cycles (i.e., the one which is achieved first) subjected to a maximum of 100 cycles.

V. SIMULATION RESULTS ANDDISCUSSIONS

The developed AIS optimization technique was employed to determine the scheduling maintenance for 21 generatorunits over a planning period of one year. The design of these approaches to give the best performance in terms of finding good solutions to the test GMS problem has been established after extensive experimentation. The performances of Clonal algorithmfordifferentvaluesofcrossoverprobability(CP)and mutation probability (MP) were first investigated. In each case ten independent Clonal algorithm runs were done, using a different random initial population for each run, but the same ten initial populations for each case. The table: 1 gives the capacities, allowed period and duration of maintenance and the manpower required for each unit. The power system peak load is 4739 MW, and there is 20 technical staff available for maintenance work in each week. The allowed period for each generator is the result of a technical assessment and the experience of the maintenance personnel, which ensures adequate maintenancefrequency.

The population size was taken to be 100, and the total number of iterations (new solutions) for each run was 3000. The performances of Clonal algorithm were found to be stable for a range of values of CP and MP. For Clonal algorithm the best performance, in terms of the average over ten runs of the evaluation value of the best solution, was found with CP = 0.5, MP = 0.05. The best solution obtained from Clonal algorithm given the highest reliability measure with SSR = 132.95 × 105 shown in Fig 3 and the crew constraint was limited to maximum of 30 shown in Fig 4. It is important to note from this figure that the crew demand inversely related with the load availability over the entire maintenance period. The applications of GA, SA and GA/heuristic hybrid to the test GMS problem are discussed the methodology. These methods use the integer encoding and the evaluation function.

The discussion about these applications is relatively limited in this paper; a fuller description is given in previous works [2]. The total number of iterations for each run of the SA and GA methods has been set to 30,000, which was determined by an empirical analysis of the convergence of these methods. These methods have been implemented using the Reproductive Plan Language, RPL2 [11]. GA/SA/heuristic hybrid was found that seeding a heuristic solution to the initial population pool improved the GA performance. It was also observed in the previous section that the GA/SA approach is less sensitive to the variation of technique parameters. The steady state population updating structure with population size = 100, CP = 1.0, MP= 0.05. This observation is consistent with the GA/heuristicperformance.However,thevariationintheresults obtainedwiththeGA/SA/heuristicwaslessthanthatobtained with the GA/heuristic. The GA/SA/heuristic hybrid approach has measured the SSR = 139.10×10^5 and the TMV = 40.

Table I. **Data for the test system**

Unit	Capacity (MW)	Allowed period	Outage (weeks)	Manpower required for each week
1	555	1-26	7	10+10+5+5+5+5+3
2	555	27-52	5	10+10+10+5+5
3	180	1-26	2	15+15
4	180	1-26	1	20
5	640	27-52	5	10+10+10+10+10
6	640	1-26	3	15+15+15
7	640	1-26	3	15+15+15
8	555	27-52	6	10+10+10+5+5+5
9	276	1-26	10	3+2+2+2+2+2+2+2+2+3
10	140	1-26	4	10+10+5+5
11	90	1-26	1	20

12	76	27-52	3	10+15+15
13	76	1-26	2	15+15
14	94	1-26	4	10+10+10+10
15	39	1-26	2	15+15
16	188	1-26	2	15+15
17	58	27-52	1	20
18	48	27-52	2	15+15
19	137	27-52	1	15
20	469	27-52	4	10+10+10+10
21	52	1-26	3	10+10+10

Table II comparison of results obtained using different methodology for SA, GA, GA/Heuristic Hybrid, GA/SA Hybrid, GA/SA Heuristic Hybrid and Fuzzy logic gives the sumofsquareofreservegenerationandcrewconstraints. Crew constraint is greater than 30. We assume that hiring such large extra manpower is not economic for the power utility. The schedules represented by these solutions are depicted in Figs. 2 show the reserve margins for these schedules, which are non- negative since all three schedules satisfy the load constraint. The manpower requirements for these solutions are shown in Fig. 3 in which the vertical bar (25 - 28, 31 and 49th weeks), there are no manpower is required. We will give another work at the period. As explained above the utility can hire about 5% extramanpoweriftheincreaseinthereliabilitycosteffective.

***Table* II.ComparsionOfResultsObtainedUsingDifferentMethods**

	SSR(x10^5)	**TMV**
SA	140.06	40
GA	137.91	40
GA/Heuristic Hybrid	139.96	40
GA/SA Hybrid	138.12	40
GA/SA/ Heuristic Hybrid	139.10	40
Fuzzy Logic	133.40	37
Clonal Algorithm	132.95	30

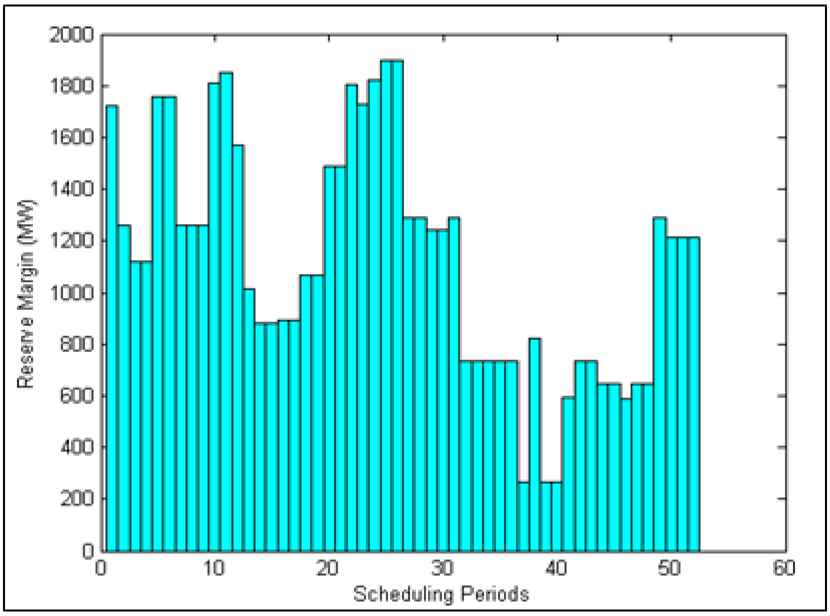

Figure 2: Reserve margin for the best solution obtained from Clonal algorithm

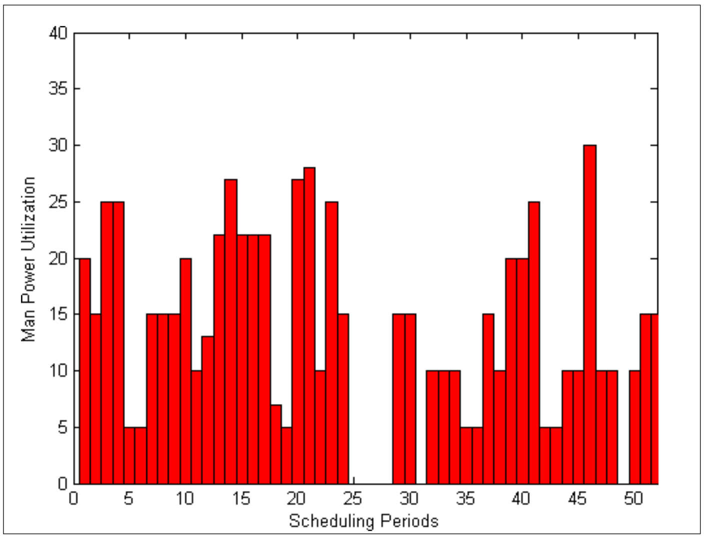

Figure 3: Manpower allocations for the best solution obtained from Clonal algorithm

VI. CONCLUSIONS

The problem of generating optimal preventive maintenance schedule of generating units for economical and reliable operation of a power system while satisfying system load demand and crew constraints over a half year period has been presented on a 21-unit test system. The integration of the mutation operator in the clonal algorithm improved the particles diversity and avoided the premature convergence problem effectively, and also showed good optimization performance. It copes with continuous and discrete variables conveniently. The results reflect a feasible and practicaloptimal solution that can be implemented in real time. Future work is to test on a large test system having different specifications over to a composite power system. The resulting optimal schedules will form part of overall system planning operationofapowerutility.Futureworkwillalsoseektomake the mutation operation adaptive while other powerful variants could be integrated into the clonal algorithm to improve the presentperformance.

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