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Reduction of Real Power Loss and Safeguarding of Voltage Constancy by Artificial Immune System Algorithm

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Abstract

In this paper, Artificial Immune System (AIS) algorithm is used for solving reactive power problem. Artificial Immune System Algorithm, also termed as the machine learning approach to Artificial Intelligence, are powerful stochastic optimization techniques with potential features of random search, hill climbing, statistical sampling and competition. Artificial immune system algorithmic approach to power system optimization these ideas are embedded into proposed algorithm for solving reactive dispatch problem.In order to evaluate the proposed algorithm, it has been tested in standard IEEE 30,118 bus systems and compared to otherspecified algorithms. Simulation results show better performance of the proposed AIS algorithm in reducing the real power loss and preservation of voltage stability.

Keywords*: Antibody, Antigen, Cloning, Hyper mutation, Optimization, optimal reactive power, Transmission loss*

1. Introduction

Optimal reactive power dispatch (ORPD) problem is to minimize the real power loss and bus voltage deviation. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered as a set of linear functions which mostly lead to loss of accuracy. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. Leandro Nunes de Castro & Fernando J.Von Zuben et al [21] had presented the clonal selection algorithm is used by the natural immune system to define the basic features of an immune response to an antigenic stimulus. It establishes the idea that only those cells that recognize the antigens are selected to proliferate. The selected cells are subject to an affinity maturation process, which improves their affinity to the selective antigens. In this paper, we propose a powerful computational implementation of the clonal selection principle that explicitly

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takes into account the affinity maturation of the immune response. The algorithm is shown to be an evolutionary strategy capable of solving complex machine learning tasks, like pattern recognition and multimodal optimization. The performance of AIShas been evaluated in standard IEEE 30,118 bus test systemsand the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}\right) \quad (1)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (2)$$

where gk : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. Pd: is the total active power demand, Pgi: is the generator active power of unit i, and Pgsalck: is the generator active power of slack bus.

Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (3)$$

where ωv: is a weighting factor of voltage deviation.
VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (4)$$

Equality Constraint

The equality constraint of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (5)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

Inequality Constraints

The inequality constraints reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (6)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (7)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (8)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (9)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \quad (10)$$

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

2. Research method

The immune system (IS) is a complex of cells, molecules and organs that represent an identification mechanism capable of perceiving and combating dysfunction from our own cells (infectious self) and the action of exogenous Infectious microorganisms (infectious oneself). The interaction among them IS and several other systems and organs allow the regulation of the body, guaranteeing its stable functioning. Without the immune system, death from infection would be inevitable. Its cells and molecules maintain constant surveillance for infecting organisms. They recognize an almost limitless variety of infectious. Foreign cells and substances, known as non-self-elements, distinguishing them from those native Non-infectious cells, known as self-molecules. When a pathogen (infectious foreign element) enters the body, it is detected and mobilized for elimination. The AIS can be defined as a computational system based upon metaphors of the biological immune system. The immune engineering (IE) is a meta-synthesis process that uses the information contained in the problem itself to define the solution tool to a given problem, and then apply it to obtain the problem solution. It is not our intention to pose a strict limit between the AIS and the IE. Instead, we intend to make use of all immunological inspired phenomena and algorithm in order to solve complex problems.

The topics involved in the definition and development of the artificial immune systems cover mainly:

a) Hybrid structures and algorithms that take into account immune-like mechanisms.
b) Computational algorithms based on immunological principles, like distributed processing, clonal selection algorithms, and immune network theory.
c) Immunity-based optimization, learning, self-organization, artificial life, cognitive models, multi-agent systems, design and scheduling, pattern recognition and anomaly detection.
d) Immune engineering tools. Potential applications of the artificial immune systems can be listed (but are not limited to): Pattern recognition, function approximation and optimization, anomaly detection, computer and network security, generation of diversity and noise tolerance.

The stepwise procedure of AIS for the Optimization problem can be outlined as follows:

i. Read the data which includes maximum and minimum limits and population size etc.
ii. Generate random binary string
iii. Decode them to actual value
iv. Insert them in population pool
v. Check for the satisfaction of constraints of the objective function if ‘yes’ go to (vi) else go to (i).
vi. Evaluate fitness.
vii. Select the antigen and antibody from the fitness values.
viii. Calculate the Euclidean distance between antibody and antigen.
ix. If D is more select them for hyper mutation else simple mutation by cloning the antibody.
x. Enter the cloned population in new Population pool.
xi. Check for the satisfaction of constraints of the objective function.
xii. Check for the convergence else go to clonal proliferation.

AIS are inspired by the human immune system which is a highly evolved, parallel and distributed adaptive system that exhibits the following strengths: immune recognition, reinforcement learning, feature extraction, immune memory, diversity and robustness. The artificial immune system (AIS) combines these strengths and has been gaining significant attention due to its powerful adaptive learning and memory capabilities. The main search power in AIS relies on the mutation operator and hence, the efficiency deciding factor of this technique. The steps in AIS are as follows:

1. Initialization of antibodies (potential solutions to the problem). Antigens represent the value of the objective function f(x) to be optimized.
2. Cloning: where the affinity or fitness of each antibody is determined. Based on this fitness the antibodies are cloned; that is the best will be cloned the most. The number of clones generated from the n selected antibodies is given by: Nc =Σ round (β*j/i) i = 1,2…….n , Where Nc is the total number of clones, β is a multiplier factor and j is the population size of the antibodies.
3. Hyper mutation: The clones are then subjected to a hyper mutation process in which the clones are mutated in inverse proportion to their affinity; the best antibody‘s clones are mutated lesser and worst antibody‘s clones are mutated most. The clones are then evaluated along with their original antibodies out of which the best N antibodies are selected for the next iteration. The mutation can be uniform, Gaussian or exponential.

Initialisation / Encoding

Along with other heuristics, choosing a suitable encoding is very important for the algorithm's success. Similar to Genetic Algorithms, there is close inter-play between the encoding and the fitness function (in AIS referred to as the 'matching' or 'affinity' function). Hence, both ought to be thought about at the same time. For the current discussion, let us begin with the encoding. First, let us define what is meant by 'antigen' and 'antibody' in the context of an application domain. Typically, an antigen is the 'target', e.g. the data item to be checked to see if it is an intrusion, or the user to be clustered or made a recommendation for. The antibodies are the remainder of the data, e.g. other users in the database, general network traffic that has already been identified etc. Sometimes, there can be more than one antigen at a time and there are usually a large number of antibodies present simultaneously. Antigens and antibodies are represented or encoded in the same way. For most problems the most obvious representation is a string of numbers or features, where the length is equal to the number of variables, the position is the variable identifier and the value is the actual value of the variable itself (e.g. binary or real).

Similarity or Affinity Measure (Fitness Function)

As mentioned above, similarity measures or matching rules are very important design choices in developing an AIS algorithm, and closely coupled to the encoding scheme .Two of the simplest matching algorithms are best explained using binary encoding: Consider the strings (00000) and (00011). If one does a bit-by-bit comparison, the first three bits are identical and hence one could give this pair a matching score of 3. In other words, one computes the opposite of the Hamming Distance (which is defined as the number of bits that have to be changed in order to make the two strings identical). Now consider this pair: (00000) and (01010). Again, simple bit matching gives us a similarity score of 3. However, the matching is quite different as the three matching bits are not connected. Depending on the problem and encoding, this might be better or worse. Thus, another simple matching algorithm is to count the number of continuous bits that match and return the length of the longest matching as the similarity measure. For the first example above, this would still be 3, for the second example this would be 1. If the encoding is non-binary, e.g. real variables, there are even more possibilities to compute the 'distance' between the two strings, for instance one could compute the geometrical (Euclidian) distance etc.

The target user is encoded as the antigen, and all other users in the database are possible antibodies. We add the antigen to the AIS and then we add one candidate antibody at a time. Antibodies will start with a certain concentration value. This value represents the natural lifespan of antibodies and decreases over time (death rate), similar to the evaporation in Ant Systems. Antibodies with a sufficiently low concentration are removed from the system, whereas antibodies with a high concentration may saturate. An antibody can increase its concentration by matching the antigen: The better the match the higher the increase (a process called 'stimulation'). The process of stimulation or increasing concentration can also be regarded as 'cloning' if one thinks in a discrete setting. Once enough antibodies have been added to the system, it starts to iterate a loop of suppression and stimulation until at least one antibody drops out. A new antibody is then added and the process is repeated until the AIS has stabilised, i.e. until there are no more drop-outs for a certain period of time. Mathematically, in each step (iteration) an antibody's concentration is increased by an amount dependent on its matching to the antigen. In the absence of matching, an antibody's concentration will slowly decrease over time. Hence, AIS iteration is governed by the following

$$\frac{dx_i}{dt} = [(\text{antigens recognised}) - (\text{death rate})] = \left[k_2 \left(\sum_{j=1}^{N} m_{ji} x_i \, y_i\right) - k_3 \, x_i\right] \quad (11)$$

Where:
N is the number of antigens.
xi is the concentration of antibody we
yj is the concentration of antigen j
k2 is the stimulation effect and k3 is the death rate
mji is the matching function between antibody we and antibody (or antigen) j.

AIS Algorithm for reactive power problem

input : S = set of patterns to be recognized, nt network affinity threshold, ct clonal pool threshold, h number of highest affinity clones, a number of new antibodies to introduce
output : N = set of memory detectors capable of classifying unseen patterns

begin

Create an initial random set of network antibodies, N
repeat

for all patterns in S do
Determine the affinity with each antibody in N
Generate clones of a subset of the antibodies in N with the highest affinity. The number of clones for
an antibody is proportional to its affinity
Mutate attributes of these clones to the set A , a and place h number of
the highest affinity clones into a clonal memory set, C
Eliminate all elements of C whose affinity with the antigen is less than a predefined threshold ct
Determine the affinity amongst all the antibodies in C and eliminate those antibodies whose affinity with each
other is less than the threshold ct

Incorporate the remaining clones of C into N
end

Determine the affinity between each pair of antibodies in N and eliminate all antibodies whose affinity
is less than the threshold nt
Introduce a random number of randomly generated antibodies and place into N
end until a stopping criteria has been met
end .

3. Results and Discussions

At first AIS algorithm has been tested on the IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The considered security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table 1.

Table 1. Initial Variables Limits (PU)

Control variables	Min. value	Max. value	Type
Generator: Vg	0.92	1.11	Continuous
Load Bus: VL	0.94	1.02	Continuous
T	0.94	1.02	Discrete
Qc	-0.11	0.31	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table 2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

Table 2. Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3. Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	AIS
V1	1.0641
V2	1.0553
V5	1.0309
V8	1.0423
V11	1.0849
V13	1.0649
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10
Q24	0.10
PLOSS	4.5208
VD	0.9076

The proposed approach succeeds in keeping the dependent variables within their limits as shown in table 3.

Table IV summarizes the results of the optimal solution and it reveals the reduction of real power loss after optimization.

Table 4. Comparison Results of Different Methods

Methods	Ploss (MW)
SGA (22)	4.98
PSO (23)	4.9262
LP (24)	5.988
EP (24)	4.963
CGA (24)	4.980
AGA (24)	4.926
CLPSO (24)	4.7208
HSA (25)	4.7624
BB-BC (26)	4.690
AIS	4.5208

Secondly AIS has been tested in standard IEEE 118-bus test system [28]. The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting

transformers. The line and bus data and their limits are given in [www.ee.washington.edu/trsearch/pstca]. The limits of voltage on generator buses are 0.95-1.1 per-unit., and on load buses are 0.95-1.05 per-unit. The limit of transformer rate is 0.9-1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 5, with the change step of 0.01.

Table 5. Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

In this case, the number of population is increased to 120 to explore the larger solution space. The total number of generation times is set to 200. The statistical comparison results of 50 trial runs have been list in Table 6 and the results clearly show the better performance of proposed algorithm.

Table 6. Comparison of simulation results in 118-bus system

Active power loss (p.u)	BBO [27]	ILSBBO/ strategy1 [27]	ILSBBO/ strategy1 [27]	Proposed AIS
min	128.77	126.98	124.78	120.87
max	132.64	137.34	132.39	131.56
Average	130.21	130.37	129.22	128.01

4. Conclusion

In this paper a novel approach AIS algorithmhas been sucessfully solved optimal reactive power problem.Performance comparisons with well-known population-based algorithms gives encouraging results. AIS emerges to find good solutions when compared to that of other algorithms. The simulation results presented in previous section prove the ability of AIS approach to arrive at near global optimal solution.

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