An Artificial Immune System Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract

This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in a power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. This paper presents artificial immune system for solving above 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.

Key words —Modal analysis, optimal reactive power, Transmission loss, Optimization, Antibody, Antigen, Cloning, Hyper mutation, Optimization.

1. Introduction

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1-2], Newton method [3] and linear programming [4-7].The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input-output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently global Optimization techniques such as genetic algorithms

have been proposed to solve the reactive power flow problem [8, 9].

Leandro Nunes de Castro & Fernando J.Von Zuben [10] 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 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 effectiveness of the proposed approach is demonstrated through IEEE-30 bus system. The test results show the proposed algorithm gives better results with less computational burden and is fairly consistent in reaching the near optimal solution

In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [11]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [12] is used as the indicator of voltage stability.

2. Voltage Stability Evaluation

2.1. Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing eigen values and right and left eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=\begin{bmatrix}J_{p\theta}J_{PV}\\ J_{Q\theta}J_{QV}\end{bmatrix}\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \qquad (1)$$

Where

ΔP = Incremental change in bus real power.
ΔQ = Incremental change in bus reactive Power injection
$\Delta\theta$ = incremental change in bus voltage angle.
ΔV = Incremental change in bus voltage Magnitude

$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q=[J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}]\Delta V = J_R \Delta V \quad (2)$$

$$\Delta V = J^{-1}\Delta Q \qquad (3)$$

Where

$$J_R= (J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J PV) \qquad (4)$$

J_R is called the reduced Jacobian matrix of the system.

2.2. Modes of Voltage instability

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors

Let

$$J_R = \xi \Lambda \eta \qquad (5)$$

Where,
ξ = right eigenvector matrix of J_R
η = left eigenvector matrix of J_R
Λ = diagonal eigenvalue matrix of J_R and

$$J_R^{-1} = \xi \Lambda^{-1} \eta \quad (6)$$

From (3) and (6), we have

$$\Delta V = \xi \Lambda^{-1} \eta \, \Delta Q \quad (7)$$

Or

$$\Delta V = \sum_i \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \quad (8)$$

where ξ_i is the ith column right eigenvector and η the i^{th} row left eigenvector of J_R.

λ_i is the ith eigen value of JR.

The i^{th} modal reactive power variation is,

$\Delta Q_{mi} = K_i \xi_i$ (9)

Where,

$$K_i = \sum_j \xi_{ij}^2 - 1 \quad (10)$$

Where

ξ_{ji} is the jth element of ξ_i

The corresponding i^{th} modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi} \quad (11)$$

It is seen that, when the reactive power variation is along the direction of ξ_i the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the i^{th} eigenvalue. In this sense, the magnitude of each eigenvalue λ_i determines the weakness of the corresponding modal voltage. The smaller the magnitude of λ_i, the weaker will be the corresponding modal voltage. If $|\lambda_i| = 0$ the i^{th} modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the k^{th} one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k} \xi_1}{\lambda_1} \quad (12)$$

where η_{1k} the k^{th} element of η_i.

V - Q sensitivity at bus k,

$$\frac{\partial V_k}{\partial Q_k} = \sum_i \frac{\xi_{ki} \eta_{ik}}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \quad (13)$$

A system is voltage stable if the eigenvalues of the Jacobian are all positive. Thus the results for voltage stability enhancement using modal analysis for the reduced jacobian matrix is when

eigen values $\lambda i > 0$, the system is under stable condition

eigen values $\lambda i < 0$, the system is unstable

eigen values $\lambda i = 0$, the system is critical and collapse state occurs

3. Problem Formulation

3.1.Nomenclature

N_B number of buses in the system

N_g number of generating units in the system

t_k tap setting of transformer branch k

P_{sl} real power generation at slack bus

V_i voltage magnitude at bus i

P_i, Q_i real and reactive powers injected at bus i

P_{gi},Q_{gi} real and reactive power generations at bus i

G_{ij},B_{ij} mutual conductance and susceptance between bus i and j

G_{ii},B_{ii} self conductance and susceptance of bus i

θ_{ij} voltage angle difference between bus i and j

The optimal reactive power dispatch problem is formulated as an optimization problem in which a specific objective function is minimized while satisfying a number of equality and inequality constraints. The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude (*gi*) *V* , reactive power generation of capacitor bank (Qci), and transformer tap setting (tk).Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows. This objective function is subjected to the following constraints:

3.2. Real power losses

To minimize the real power loss in the system, this can be expressed as

$$\text{Minimize} \quad P_{Loss} = \sum_{\substack{k \in Nl \\ k=(i,j)}} g_k \left(V_i^2 + V_j^2 - 2V_iV_j Cos\ \theta_{ij}\right) \quad (14)$$

3.3.Maximize SVSM

This is the most widely accepted index for proximity of voltage collapse. It is defined as the largest load change that the power system may sustain at a bus or collective of buses from a well defined operating point.(Base case) Using the modal analysis the minimal eigen value of the non-singular power flow jacobian matrix has been used to find the maximum static voltage stability margin in this proposed approach.

3.4.Equality Constraints

These constraints represent the typical load flow equation such as

$$P_i - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij} Cos\theta_{ij} + B_{ij} Sin\theta_{ij}\right) = 0, i \in N_B - 1 \quad (15)$$

$$Q_i - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij} Sin\theta_{ij} - B_{ij} Cos\theta_{ij}\right) = 0, i \in N_{PQ} \quad (16)$$

3.5.Inequality Constraints

These constraints represent the system operating constraints. Generator bus voltages (Vgi), reactive power generated by the capacitor (Qci), transformer tap setting (tk), are control variables and they are self restricted. Load bus voltages (Vload) reactive power generation of generator (Qgi) and line flow limit (Sl) are state variables, whose limits are satisfied by adding a penalty terms in the objective function. These constraints are formulated as

(i) Voltage limits

$$V_i^{\min} \le V_i \le V_i^{\max} \ ; i \in N_B \quad (17)$$

(ii) Generator reactive power capability limit

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} ; i \in N_g \quad (18)$$

(iii) Capacitor reactive power generation limit

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} ; i \in N_c \quad (19)$$

(iv) Transformer tap setting limit

$$t_k^{\min} \le t_k \le t_k^{\max} ; k \in N_T \quad (20)$$

(v) Transmission line flow limit

$$S_l \leq S_l^{\max} ; l \in N_l \qquad (21)$$

The equality constraints are satisfied by running the power flow program. The active power generation (Pgi), generator terminal bus voltages (Vgi) and transformer tap settings (tk)
are the control variables and they are self restricted by the optimization algorithm. The active power generation at slack bus (Psl), load bus voltage (Vload) and reactive power generation (Qgi) are the state variables and are restricted by adding a quadratic penalty term to the objective function.

4. Artificial Immune System (AIS)

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.

Artificial Immune algorithm Proposed by Dasgupta , in 1999 [13], is based on clonal selection principle and is a population based algorithm .AIS is 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: $Nc = \Sigma$ round $(\beta * j/i)$ 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.

4.1. *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).

4.2. 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

$$\frac{dx_i}{dt} = \left[\begin{pmatrix} antigens \\ recognised \end{pmatrix} - \begin{pmatrix} death \\ rate \end{pmatrix}\right] = \left[k_2 \left(\sum_{j=1}^{N} m_{ji} x_i y_j\right) - k_3 x_i \right] \quad (22)$$

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.

4.3. The Algorithm

input : S = set of patterns to be recognised, *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

forall 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 .

The AIS is considered stable after iterating ten times without changing in size. Stabilisation thus means that a sufficient number of 'good' neighbours have been identified and therefore a prediction can be made. 'Poor' neighbours would be expected to drop out of the AIS after a few iterations. Once the AIS has stabilised using the above algorithm, we use the antibody concentration to weigh the neighbours and then perform a weighted average type recommendation.

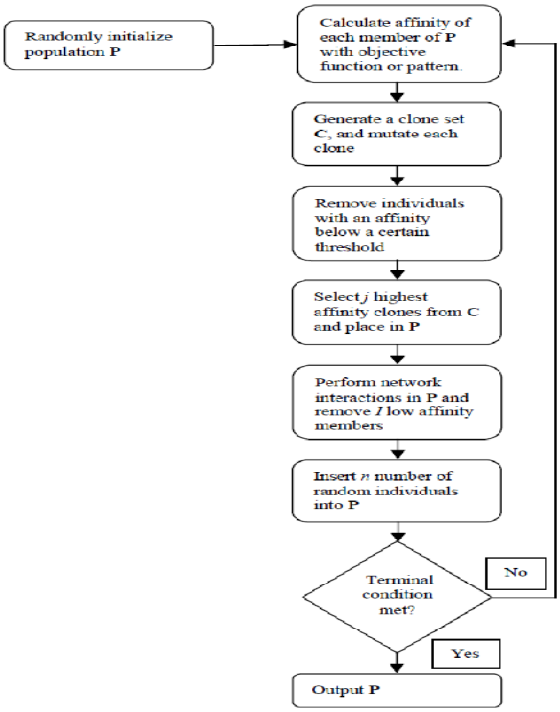

Fig 1.Flow Chart of Immune Network Algorithm

5. Simulation Results

The validity of the proposed Algorithm technique is demonstrated on IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The real power settings are taken from [1]. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus. The results of the simulations are presented in below Tables I, II, III .

TABLE I: Voltage Stability under Contingency State

Sl.No	Contigency	ORPD Setting	Vscrpd Setting
1	28-27	0.1400	0.1422
2	4-12	0.1658	0.1662
3	1-3	0.1784	0.1754
4	2-4	0.2012	0.2032

TABLE II: Limit Violation Checking of State Variables

State variables	limits		ORPD	VSCRPD
	Lower	upper		
Q1	-20	152	1.3422	-1.3269

Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

TABLE III: Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming[16]	5.0159
Genetic algorithm[17]	4.665
Real coded GA with Lindex as SVSM[18]	4.568
Real coded genetic algorithm[19]	4.5015
Proposed AIS method	4.4695

6. Conclusion

In this paper a novel approach based on artificial immune system (AIS) algorithm to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied.
The proposed method formulates reactive power dispatch problem as a mixed integer non-linear optimization problem and determines control strategy with continuous and discrete control variables such as generator bus voltage, reactive power generation of capacitor banks and on load tap changing transformer tap position. To handle the mixed variables a flexible representation scheme was proposed. The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system

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