Artificial Immune-Based For Voltage Stability Prediction In Power System

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Abstract
Voltage instability has recently become a challenging problem for many power system operators. This r blackouts. This paper presents the application of Artificial Immune Systems (AIS) for online voltage stability evaluation that could be used as early warning system to the power system operator so that necessary action could be taken in order to avoid the occurrence of voltage collapse. Key features of the proposed method are the implementation of clonal selection principle that has the capability in performing pattern recognition task. The proposed technique was tested on the IEEE 30 bus power system and the results shows that fast performance with accurate prediction for voltage stability condition of the system was obtained. In order to realize the superior features of AIS, a comparative study was conducted with Artificial Neural Network (ANN)-based prediction system. This system was developed to perform similar task on the same test system.

Keywords: *Artificial Immune Systems, Pattern Recognition, Voltage Stability.*

1. Introduction
Voltage stability is the ability of a power system to maintain steadily acceptable bus voltage at each node under normal operating conditions, following load increases, system configuration changes or a disturbance. The progressive and uncontrollable drop in voltage eventually results in a wide spread voltage collapse.

Problems related to voltage stability issues have attracted greater concern among the power system engineers since power systems nowadays have evolved through continuing growth in interconnection and operating in highly stressed condition[1]. Therefore voltage stability evaluation becomes part of the power system operation routine and has been treated by a wide spectrum of computational approaches with major goal of determining the voltage stability condition of the system and its margin from instability condition [2]. A fast method to evaluate voltage stability condition is desirable

phenomenon has been reported to be responsible for severe low voltage condition leading to majo

since rapid action and accurate decision is needed so that the occurrence of voltage collapse could be avoided.

Nowadays, power system control and operation has made use of intelligent systems in determining system condition for the on line monitoring system. This is due to their capability in giving fast decision or prediction with acceptable accuracy. The applications of intelligent systems have been reported to solve power system problems since early 1980's [3]. Expert System (ES) and Artificial Neural Network (ANN) are the most common intelligent systems employed in solving various problems in power system operation and planning [3]. The learning capability of ANN has been exploited for power system security prediction as reported in references [4-7]. For example, a multi-layer feed-forward perceptron ANN was implemented for evaluating power system dynamic stability as described in reference 4. This method utilized the most critical eigenvalue obtained from the S-matrix as the indicator or index to power system dynamic stability and taken to be the output of the ANN. The relationship between the index (output) and the input quantities (nodal active and reactive power, nodal voltage magnitudes and angles) are represented as a three-layer feed-forward neural network. The neural network was constructed with the back propagation algorithm. On the hand, a supervised clustering algorithm of neural network was used to assess the dynamic stability as mentioned in reference [5]. The algorithm implemented the adaptive threshold valued to the traditional clustering method and used the supervised output as the convergence constraints. The technique has able to reduce the training time of the neural network. In reference 6, ANN was used to predict the frequency of the centre of inertia during the first ten seconds of a dynamic process after the occurrence of generator outage. The prediction from the developed ANN would help the power system operator to decide whether or not load shedding should take place using the structure of the steady-state security assessment model.

Another application of ANN for power system security evaluation is described in reference 7. This paper presented an ANN based methodology to assess the steady state security of a power system. The system's voltage level was assessed by the neural network on real time basis in order to determine the system vulnerability.

Artificial immune systems can be defined as metaphorical systems inspired from the human immune system [8]. The natural immune system is a very complex system with several mechanisms to protect our bodies from attack from foreign bodies called antigens. The main purpose of the immune system is to recognize all cells within the body and categories those cells as either self or nonself. The immune system learns 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 and classification tasks. Particularly, it learns to recognize relevant patterns, remember patterns that have been seen previously to construct pattern detectors efficiently [9]. A few computational models have been developed based on several principles of the immune system such as immune network model, negative selection algorithm, positive selection algorithm and clonal selection principle [10,11].

This paper presents an application of Artificial Immune System (AIS) using clonal selection principle to predict the voltage stability condition in a power system. The qualities of AIS lay in its pattern recognition and memorization capabilities [12]. Motivations of applying AIS for predicting voltage stability condition in a power system are:

1. Its fast computation capability for voltage insecurity detection, which is required for real-time monitoring.
2. Populations of antibodies are operated simultaneously, thereby decreasing the possibilities of computation process stagnation [12].
3. This newly discovered technique could act as a useful alternative in addition to other existent methods in solving pattern recognition-related-problems.

In order to offer effective defense functions, an immune system must accomplish the pattern recognition tasks such that the self-modules and cells can be distinguished from foreign ones (antigens). With the memorization capability of the immune system, the response of the second encounter to the same antigen can be seen more vigorous than that of the first encounter. These distinct features are depicted in the AIS and solidify the performance of immune-based computation. Through the immunology evolution, feasible antibodies to the antigen can be produced. With the aid of affinity calculations, the combination intensity between antigen and antibody is measured, which also guide the suppression of antibody generations. After meeting the generation limit of AIS computation, a set of memory cells that contain antibodies that most fits the antigens is considered as a solution to this problem.

2. Artificial Immune System (AIS)

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 (or molecules) within the body and categorize those cells as self or non-self. The non-self cells are further categorized in order to induce an appropriate type of defensive mechanism. The immune system learns through evolution to distinguish between dangerous foreign antigens and the body's own cells or molecules.

Our body maintains a large number of immune cells-called lymphocytes, which circulate throughout the body. There are mainly two types of lymphocytes; T cells and B cells. These two types of lymphocytes play different roles in the immune response, though they may act together and control or affect one another's function. For example, T cells can either enhance or suppress the B cells' response to a stimulus. When an antigen invades the body, only a few of these immune cells can recognize the invader's peptides.' This recognition stimulates proliferation and differentiation of the cells that produce matching clones (or antibody). This process, called the clonal expansion, generates a large population of antibody-producing cells that are specific to the antigen. The clonal expansion of immune cells results in destroying or neutralizing the antigen [13]. Some of these cells are retained in the immunological memory, so that any subsequent exposure to a similar antigen leads to rapid immune response (secondary response).

A system using the concept of AIS is developed in this study following the clonal selection theory in which used to predict the voltage stability condition of a power system. The algorithm for the clonal selection theory is as follows [13]:

1. Randomly generate an initial population of antibodies Ab. This is composed of two subsets Ab_m (memory population) and Ab_r (reservoir population)
2. Create a set of antigenic patterns Ag.
3. Select an antigen Ag_i from the population of antigen Ag.
4. For every member of the antibody population Ab, calculate its affinity with respect to the antigen Ag_i using the Euclidean Distance function.
5. Select n antibodies of highest affinity and generate c clones for each antibody in proportion to their affinity value and place the clones in a new population C_i.
6. Mutate the clone population C_i to a degree inversely proportional to their affinity value in order to produce a mature population C_{im}.
7. Re-apply the affinity function to each member of the population C_{im}.
8. Select from C_{im} the candidate with highest score as the candidate for memory cell. If its affinity value is greater than affinity value of the current memory cell Ab_{mi}, then the candidate becomes the new memory cell.
9. Remove those antibodies with low affinity values in the population Ab_r and replace them with new randomly generated members.

10. Repeat steps 3-9 until all antigens have been presented. This represents one generation of the algorithm.

The whole is repeated until meeting the stopping criterion of AIS computation is met. The final set of memory cells contains the antibodies that most fits the antigens which are used to perform the prediction task.

A. Affinity Measurement

In order to get the affinity value between antibody (possible solution) and antigen (pattern to be recognized), Euclidean Distance function is used. Given two points $x = (x_1, x_2)$ and $y = (y_1, y_2)$, the distance between both points can be calculated using following equation :

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \qquad (1)$$

and the value of affinity is :

$$f = \frac{1}{d} \qquad (2)$$

B. Cloning

The cloning process is done independently and proportionally to their antigenic affinity. It would means that higher number of clones will be produced from the antibodies with higher antigenic affinity. The number of clones to be produced by each antibody during the cloning process is given by equation 3.

$$c = \left[0.1 - \frac{f_i}{\sum_{i=1}^{i=b} f_i} \right] \times \mathrm{m} \qquad (3)$$

b = number of antibody to be cloned

m = number of pattern to be recognised

f_i = affinity

C. Mutation

Two types of mutation technique are used in this study, which are Gaussian mutation and Cauchy mutation. The final answers from both techniques are compared and the best one is chosen as a possible solution. The mutation process is inversely proportional to the antigenic affinity; the higher the affinity, the smaller the mutation rate.

D. Regression Test

The regression test was conducted in order to determine the accuracy of the predicted voltage stability condition after the testing process,. Regression test is a process of measuring how well the trend in the predicted values following the profile of the past actual value. Therefore, it is a measure of how well the predicted values from a forecasted model "fit" with the real-life data [14]. The regression test will produce a value called regression value or also known as the correlation coefficient, R.

The correlation coefficient is a number between 0 and 1. If there is no relationship between the predicted values and the actual values, the correlation coefficient is 0 or very low. On the other hand, the correlation coefficient value approaches 1.0 as the strength of the relationship between the predicted values and actual values increases. A perfect fit would give a correlation coefficient of 1.0. Thus, higher the correlation coefficient indicates better prediction.

The equation for calculating the correlation coefficient R is as follow [14] :

$$R = \frac{n\sum xy - \sum x \sum y}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right] \times \left[n\sum y^2 - \left(\sum y\right)^2\right]}} \qquad (4)$$

n = number of patterns to be tested

x = desired stability index

y = predicted stability index

Just like in other existing techniques, process of recognizing patterns involves two parts, which are training and testing. Figure 1 shows the flowchart for performing pattern recognition using the concept of Clonal Selection Algorithm (CSA) during the training process.

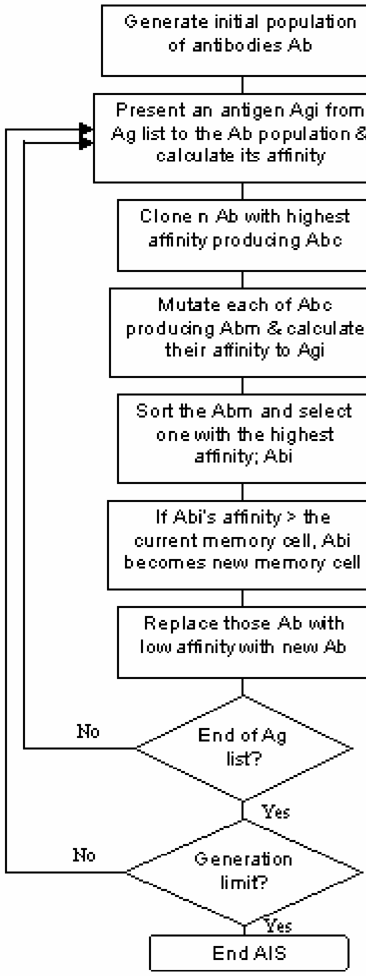

Figure 1 : Flowchart of AIS for training process

3. Voltage stability Index

There are several methods to estimate or predict the voltage stability condition of a power system. This study utilized the voltage stability index developed by Abdul Rahman et al. [15] in order to indicate the voltage stability condition at each load buses of a system. This index was derived from the voltage equation at a load bus. The voltage stability index is terms as symbol L given by[15]:

$$L_i = 4[V_{o_i} V_{L_i} \cos\theta_i - V_{L_i}^2 \cos\theta_i^{\,2}]/V_{o_i}^2 \qquad (5)$$

V_{Li} = load voltage at bus i
V_{Oi} = no load voltage at bus i
$\theta_i = (\theta_{0i} - \theta_{Li})$
θ_{Li} = load angle at bus i
θ_{0i} = no load angle at bus i

The value of L varies from 0 to 1.0. L value close to 0 indicates stable voltage condition while L value close to 1.0 indicates unstable voltage condition. In order to maintain a stable voltage condition in the system network, the value of L at any load bus must be kept to a small value close to 0. If the value of L at any load bus approaches 1.0, it shows that the load bus is close to its instability limit and if L is equal to 1.0, the system has already in the state of voltage collapse.

In this study, the value of stability index L was evaluated for every load bus in a test system for various loading conditions. Since the main objective of this work is to determine the voltage stability condition of the whole system, thus only the highest value of L is selected to represent the overall stability condition. This is because the stability of the whole system is reflected by the voltage stability condition of the most severe load bus. The highest L will then coded and grouped into 3 categories of voltage stability condition. Table 1 show the range of L corresponds to the voltage stability condition.

Table 1: Categories of voltage stability index L

Coded L	Range of L	Condition
0	0.0 – 0.5999	stable
0.5	0.6 – 0.8999	moderately stable
1.0	0.9 – 1.0	unstable / voltage collapse

4. Artificial Neural Network Solutions

In order to determine the capability of the proposed technique to predict the voltage stability condition of a power system, a comparative study was conducted by developing an Artificial Neural Network(ANN) system and used it to perform the similar task. A multilayer feedfoward Artificial Neural Network with error backporpagation learning was developed. The developed network consists of three basic elements as follows [16]:

1. Neural Network architecture
2. Suitable backpropagation learning algorithm.
3. Method of training and testing.

The topology of the developed network consists of an input layer, one hidden layer and an output layer. The input layer consists of 58 nodes meanwhile 60 nodes were used in the hidden layer. The output of this developed system is the stability index value, thus a single node was used in the output layer.

The backpropagation-based ANN was developed according the following steps :-

a. forward
b. backpropagate of error
c. weight and bias update

The training process involved in this system was performed in order to train the developed network with a set of inputs and a targeted output. Learning and momentum rates are both fixed to 0.03. Meanwhile testing process was conducted in order to get the predicted stability index by using the weights and bias obtained from the trained network.

5. Results and Discussions

The proposed method has been used for the voltage stability evaluation of the IEEE 30 bus reliability test system. The available simulation data were separated into 2 categories; training data and testing data. 122 data were used for the training process, while 40 data were utilized for the testing process.

In the proposed technique, the training process was carried out many times until it meets a stopping criterion. It was followed by the testing process using the solutions obtained from training programme, namely the configuration of the trained network and set of memory cells from ANN and AIS respectively. As shown in Figure 2 the testing procedure was executed right after the training process. This was then followed by the regression test in order to determine the accuracy of the voltage stability prediction. This cycle was repeated until the regression test gives the value of correlation coefficient higher than 0.9.

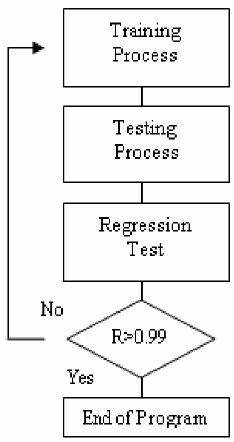

Figure 2 : Flowchart of Pattern Recognition Process

Table 2 shows the results obtained from the developed AIS-based and ANN-based voltage stability prediction systems with 40 data were used in the testing process. It could be observed from the results obtained from the AIS-based voltage stability prediction system that only one data which is the 19th was not correctly predicted. The targeted stability index is 1, conversely, the system gives the predicted value of 0.669. Meanwhile for the other testing data, the system has able to correctly predict the voltage stability condition of the system.

Table 2 : Results from the developed AIS-based and ANN-based systems

No	Actual Stability Index from AIS-based System	Targeted Stability Index	Actual Stability Index from ANN-based System
1	0.02231	0.0	0.02007
2	0.54991	0.5	0.43093
3	0.00849	0.0	0.01620
4	0.39797	0.5	0.94842
5	0.00817	0.0	0.01996
6	0.50010	0.5	0.89122
7	0.04362	0.0	0.04049
8	0.49461	0.5	0.47754
9	1.0	1.0	0.99029
10	0.04290	0.0	0.03463
11	0.99702	1.0	0.96482
12	0.02738	0.0	0.04990
13	0.99905	1.0	0.83389
14	0.04716	0.0	0.02743
15	0.99984	1.0	0.92074
16	0.02182	0.0	0.03360
17	0.99991	1.0	0.98521
18	0.00873	0.0	0.01383
19	0.66857	1.0	0.91366
20	0.00552	0.0	0.22594
21	0.50567	0.5	0.40506
22	0.99996	1.0	0.98302
23	0.00835	0.0	0.07188
24	0.50023	0.5	0.48018
25	0.99982	1.0	0.99051
26	0.00629	0.0	0.04336
27	0.51812	0.5	0.42544
28	0.01455	0.0	0.01750
29	0.50161	0.5	0.39564
30	0.00859	0.0	0.02731
31	0.01451	0.0	0.02902
32	0.99989	1.0	0.98246
33	0.00817	0.0	0.02841
34	0.49962	0.5	0.35769
35	1.0	1.0	0.95231
36	0.00554	0.0	0.04001
37	0.99853	1.0	0.94986
38	0.02231	0.0	0.02528
39	0.51878	0.5	0.57645
40	0.99909	1.0	0.95834

On the other hand, the voltage stability condition was wrongly predicted for 2 data using the ANN-based system i.e the 4th and 6th data. The performances of both systems were compared based on the correlation coefficient, RMS error of the training process and the computation time. These results are tabulated in Table 4

Table 4 : Comparison between AIS-based system and ANN-based system

Method	Correlation Coefficient R	RMS Error	Time / minute
AIS	0.99126	0.04361	13
ANN	0.96258	0.09825	11

In terms of correlation coefficient value which determines the reliability of the overall predicted stability index, AIS-based system produces a better prediction with 0.99126 of regression value. Meanwhile ANN-based system only manages to achieve 0.96258. As mentioned in section 2, the higher the correlation coefficient, the better the predicted value. AIS-based system has also shown better performance as this system is able to attain less root-mean-square error (RMS) as compared to that of the ANN-based system which are 0.04361 and 0.09825 respectively. In terms of time taken to complete the operation, ANN-based system took 11 minutes to perform its computation which is 2 minutes faster than AIS-based system.

6. Conclusion

This paper has proposed an immune-based technique for predicting the voltage stability condition of a power system. The developed system was tested using the IEEE 30 bus reliability test system and the results shows there is a good agreement between the desired output and the predicted output based on the regression analysis. The comparative study between the AIS-based system and ANN-based system shows that the AIS-based prediction system has the potential to be utilized as an alternative method in solving patter recognition-related task. In this study, the proposed technique has able to predict the voltage stability condition of a power system and therefore could be a valuable tool for fast real-time voltage stability assessment.

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