

APPLICATION OF CLONAL SELECTION IMMUNE SYSTEM METHOD FOR OPTIMIZATION OF DISTRIBUTION NETWORK

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APPLICATION OF CLONAL SELECTION IMMUNE SYSTEM METHOD FOR OPTIMIZATION OF DISTRIBUTION NETWORK

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ABSTRACT

This paper proposes an application of clonal selection immune system method for optimization of distribution network. The distribution network with high-performance is a network that has a low power loss, better voltage profile, and loading balance among feeders. The task for improving the performance of the distribution network is optimization of network configuration. The optimization has become a necessary study with the presence of DG in entire networks. In this work, optimization of network configuration is based on an AIS algorithm. The methodology has been tested in a model of 33 bus IEEE radial distribution networks with and without DG integration. The results have been showed that the optimal configuration of the distribution network is able to reduce power loss and to improve the voltage profile of the distribution network significantly.

Keywords: Artificial Intelligence; Artificial Immune System; Distribution Network; Distributed Generator.

1. INTRODUCTION

The effort to reduce the active power losses of distribution system has become an important issue in the last decade [1]–[3]. For all of the components of the electric power system, the distribution system is a component that has the greatest power losses [4]–[8]. For example, based on an energy audit by 2008, the total energy loss of electric utility in Indonesia was 16.84% [9]. By the total loss of the electrical energy, distribution system losses have recorded the biggest loss that is 14.47%, while the loss of the transmission system is only 2.37%. Therefore, in this study are discussed the efforts to

reduce the power losses of electrical energy in the distribution system. The motivation of this research is the existence of high power losses in the distribution network, as described above.

Basically, in addition to the reconfiguration of the distribution network, there are several ways to minimize the loss of electrical power distribution systems, namely the installation of capacitors, load balancing, and increasing the voltage level [10]–[14]. Installation capacitors and load balancing usually have difficulty because the load distribution system is very dynamic. Thus, the value of capacitance of the capacitor must always change

from time to time [15]-[17]. While minimizing losses by increasing the voltage level requires a high cost because all equipment is connected with this system must be able to work on a new voltage, while the result is not necessarily satisfactory [18]-[21]. Therefore, in this study focused on how the reconfiguration of power distribution network with the integration of distributed energy resources to obtain the optimal configuration of power distribution network.

In order to obtain an optimal network configuration, the previous researchers have used several methods that are classified as conventional reconfiguration methods and reconfiguration method based on artificial intelligence [22]-[28]. Conventional reconfiguration method is a method that uses a heuristic approach and classic optimization techniques [3], while the artificial intelligence based methods are simulated annealing, tabu search, artificial neural network, plant growth simulation algorithm, genetic algorithms, ant colony optimization algorithm, harmony search algorithm, particle swarm optimization algorithm, an algorithm based on fuzzy logic multi-objective, and artificial immune system algorithm [29]-[35]. The objective of this research is to optimize the configuration of distribution network using clonal selection of artificial immune system algorithm. The algorithm of artificial immune system (AIS) is a new computational algorithms inspired from the vertebrate immune system. The algorithm is able to provide the optimal solution at the end of optimization and suboptimal solutions are aware during the optimization process [3]. Methods of algorithm-based artificial immune system has the advantage of achieving the convergence of relatively rapid and computational load is low, so in this study used the clonal selection type of artificial immune system algorithm for multi-objective optimization. This study deals only with reducing network losses using configuration optimization methods. The objective functions considered are power losses and voltage profiles.

2. CLONAL SELECTION IMMUNE SYSTEM METHOD

2.1 Theory of Clonal Selection Immune System

Artificial immune system theory is used to explain the basic response of the immune system by being adaptive to antigen stimulation, as described in Figure 1. This theory states that the only cells able to recognize antigens that will proliferate, while other cells are ignored. Clonal selection

operates on B cells and T cells in cell B, when the antibody binds to the antigen then activated and differentiated into plasma cells or memory cells. Prior to this process, B cell clones are produced and undergo somatic hyper-mutation. The result obtained diversity in the population of B cells to plasma cells produce antibodies antigen-specific works against antigens. Memory cells remain with host antigens and promote secondary response quickly.

The main features of the clonal selection of artificial immune system theory are:

- a. new cells are duplicates of those parents (clone) which is charged with the rapid mutation mechanism height (somatic hyper-mutation),
- b. elimination of the new different lymphocyte making it the self-reactive receptors,
- c. proliferation and differentiation takes place through contact adult cells with antigen, and
- d. the persistence of illegal clones, resistant to early elimination by self-antigen, as the basis of the auto-immune disease.

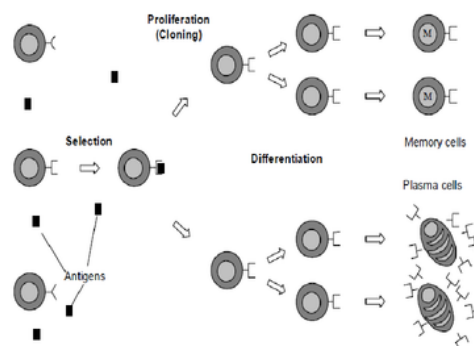


Figure 1. The General Principle Of Artificial Immune System

The analogy with natural selection fit the reality that is the strongest candidate into most cells recognizes antigens, or in other words, into cells most triggered. To workings of this algorithm, population or repertoire of receptors should be diverse enough to recognize any form of foreign cells. A mammalian immune system contains a heterogeneous repertoire of about 10^{12} lymphocytes in humans, and the rest of cells (stimulated) can display about 10^5 - 10^7 identical like-antibody receptor. Repertoire has been believed complete means that he can recognize the shape of any cell.

In [11], they have proposed the clonal selection algorithm named ClonalG for learning and optimization. They discussed the main features of the theory of clonal selection and develop algorithms include the maintenance of a set of specific memory, selection and cloning antibodies are most stimulated, death antibody non-excitatory, maturation affinity and selection of re clones are balanced against affinity antigen, and the generation and maintenance of a set of antibodies.

The main steps of clonal selection of artificial immune system method are described in the following algorithm.

```

Input: Ab, gen, n, d, L,  $\beta$ ;
Output: Ab, f
1. for t = 1 to gen,
1.1 f := decode (Ab); vector f
    contains all affinity
    antibodies that bind to the
    antigen
1.2 Abn := select (Ab, f, n);
1.3 C := clone (Abn,  $\beta$ , f);
1.4 C* := hypermut (C, f);
1.5 f := decode (C*);
1.6 Abn := select (C*, f, n);
1.7 Ab := insert (Ab, Abn);
1.8 Abd := generate (d, L);
    randomly generate antibody d
    along L
1.9 Ab := replace (Ab, Abd, f);
end;
2. f := decode (Ab); Decode
    functions are supposed to
    encode Ab and evaluation for
    values decode.
  
```

Affinity between antibody and antigen can be defined using different techniques such as matching rules and a measure of distance. One common technique used is the Euclidean distance, which is suitable when using a real-valued vector representation. To explain how ClonalG work using Euclidean distance, suppose $Ag = \{Ag_1, Ag_2, \dots, Ag_N\}$, and $Ab = \{Ab_1, Ab_2, \dots, Ab_N\}$ show the antigen and antibody sets respectively, N is the support of the order. Then, the degree of match between Ag and Ab d can be calculated based on the Euclidean distance:

$$d = \sum_{i=1}^N (Ag_i - Ab_i)^2 \quad (1)$$

Furthermore, d compared with the threshold λ , and a matching error E is obtained using the equation:

$$E = d - \lambda \quad (2)$$

If $E > 0$, it is considered that the two vectors do not match, so that these antigens are not recognized by the antibody. If $E \leq 0$, concluded that Ag Ab match, then the antigen recognized by the antibody. General range for calculation of affinity is varying between 0 and 1.

For affinity maturation, ClonalG algorithm assumes that the n highest affinity antibody is sorted rise, and the number of clones that are raised for all n selected antibodies are given by:

$$Nc = \sum_{i=1}^n \text{round} \left(\frac{\beta \cdot N}{i} \right) \quad (3)$$

with N is the total number of clones for each antigen, β are the cloned factor determining the scale factor for the number of clones for antibodies elected and β common value is $\in (0,1]$, N is the total amount of antibodies and round() is operators who rotate argument to the nearest integer. Every part of this amount corresponds to the size of clones of each antibody chosen, for example, for $N = 100$ and $\beta = 1$, antibodies highest affinity ($i = 1$) will produce 100 clones, while the antibody affinity the second highest yield of 50 clones, and thus further [11].

2.2 Clonal Selection Immune System for Reconfiguring the Distribution Network

Artificial Immune System is a computational intelligence approach that is inspired by the vertebrate immune system and has become a popular method in solving various problems in optimization. In the artificial immune system algorithm, one important variable used is the population (x), and the mutation of the population is implemented in the following equation:

$$X_{i+mj} = X_y + N(0, \beta) (X_{jmax} - X_{jmin}) (f_i/f_{max}) \quad (4)$$

Stages of completion of optimization problems using artificial immune system algorithm are based on the following steps:

Step 1. Initialize population

For the purpose of minimization of power losses, then the combination tie switches of distribution network to the condition prior to the reconfiguration should be determined in advance. Determination of the combination tie switches is done randomly. Number of tie switches is determined based on the amount of tie switches

contained in the distribution network.

Step 2. Evaluate the fitness value of each population

In order to minimize the power losses, fitness of artificial immune system is considered as a total loss in the distribution system. Total losses were evaluated by solving the power flow program. This is done by calling the power flow program into the artificial immune system as the main program. Optimizations also pay attention to the constraints of the voltage in the distribution system so that the minimum voltage and the maximum are not exceeded.

Step 3. Clone

In this process, a combination of tie switches and total power losses in the distribution network is carried out the cloning.

Step 4. The process of mutation

In this process, the value of cloning is mutated by implementing mutation carriers. Mutations only on the operator variations are used to generate offspring from each parent. Fitness of the offspring is calculated by calling the power flow program.

Step 5. Selection process

The selection process is done by applying selection strategies based on priority.

Step 6. Test the convergence

The test procedure is done to determine the convergence criteria optimization termination. Convergence criteria specified by the difference between the maximum and the minimum fitness of less than 0.0001. If the convergence condition is not met, then the process will be repeated until a convergence condition is achieved.

$$\text{maximum}_{\text{fitness}} - \text{minimum}_{\text{fitness}} \leq 0,0001 \quad (5)$$

3. RESULTS AND DISCUSSION

In this study, the optimization distribution network configuration of the 33 bus IEEE model distribution network using Clonal Selection Immune System algorithm is described. The procedure of optimization is implemented on the IEEE model of 33 bus, 12.66 kV radial distribution network in two conditions, i.e. both in without DG

integration and with DG integration. The distribution network has 33 buses and 32 sections, as shown in Figure 2. The sectionalizing switches are switches that are in closed under normal conditions while the tie switches are switches that are in open under normal conditions. Data which are loaded on 33-bus IEEE distribution network can be seen in [10]. The total load of the IEEE distribution network is 3715 kW. The base of the system is $V=12.66$ kV and $S=10$ MVA. In initial configuration, the IEEE distribution system has been set at five tie switches, i.e. switches of 33, 34, 35, 36 and 37, respectively, as can be seen in Figure 2. It also can be seen in Figure 2 that the IEEE distribution network model is consist of one feeder from a substation.

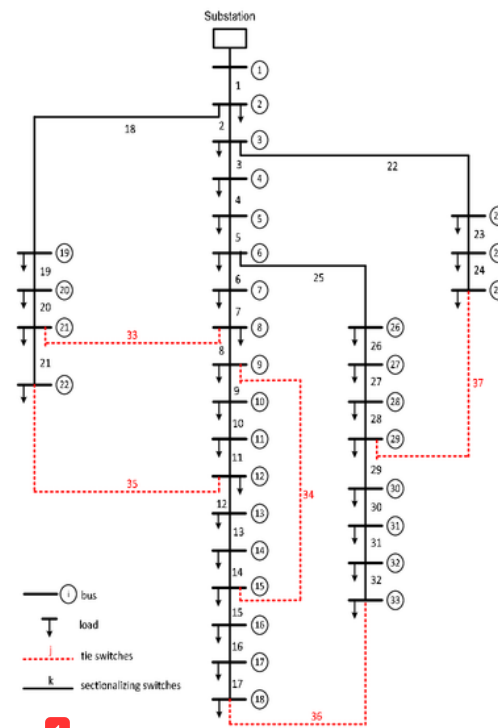


Figure 2. Initial Configuration Of A 33-Bus IEEE Distribution Network

Table 1. DG Location And Capacity Of IEEE 33-Bus System

Name	Bus Number	Active Power (MW)	Power Factor	Reactive Power (MVar)
DG1	18	1.92	0.9	0.93
DG2	22	1.75	1	0
DG3	33	1.68	0.9	0.81
Total		5.35	-	1.74

In IEEE 33-bus distribution network, there are installed as many as three DGs on buses of 18, 22, and 33. The capacities of these three DGs are 1.92 MW, 1.75 MW, and 1.68 MW, respectively, as shown in Table 1. The installation of these DGs is intended to see the impact of DG on distribution network performances.

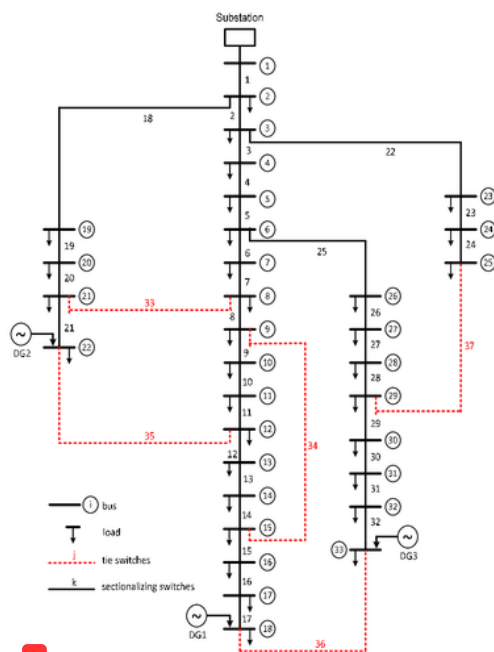


Figure 3. Integration Of Three Dgs On 33-Bus IEEE Distribution Network

The DG models that have used in our study consist of both wind farms and solar photovoltaics. We have assumed that power factor of all DG wind farms are 0.9 lagging while solar photovoltaics are unity. Integration of the three DGs on 33-bus IEEE

distribution network is shown in Figure 3. Then, the optimization of configuration of the radial distribution network model with DG integration using AIS algorithm is performed. The results of the optimization are shown in Figure 4, Figure 5, Figure 6, and Figure 7.

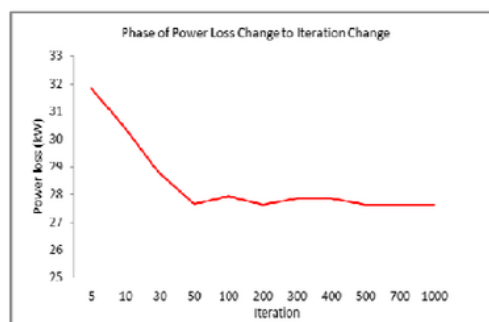


Figure 4. Phase Of Power Loss To Iteration During Optimization Process

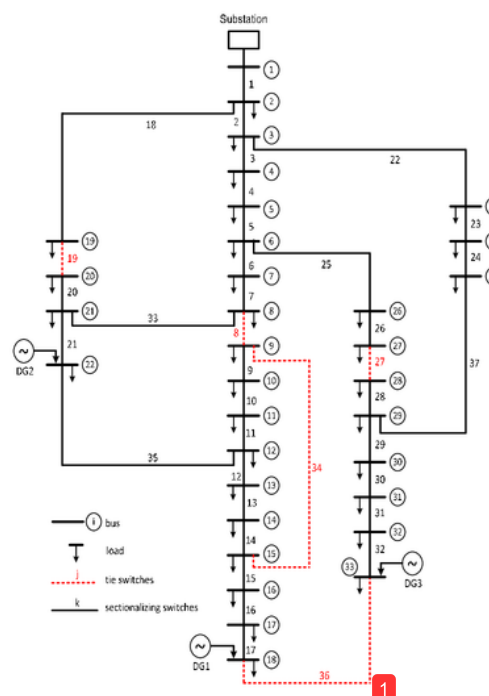


Figure 5. The Optimal Configuration Of 33-Bus IEEE Distribution Network With DG Integration

Figure 4 shows phase of power loss to iteration during optimization process of IEEE 33-bus radial

distribution network with integration of three DGs. The various iterations are applied to see the performance of AIS algorithm in optimization of distribution network configuration. Using the iterations, it is expected to be obtained information that the lowest number of iterations to get the best configuration and the lowest computation time. Optimization results show that there are as many as 9 power losses phases due to changes in iteration numbers, i.e. 5, 10, 30, 50, 100, 200, 300, 400 and 500, respectively, as can be seen in Figure 4. The optimal configuration is obtained on the iteration of 500, in computing time of 393.91 seconds. The positions of tie switches for this configuration are 8, 19, 27, 34 and 36, respectively.

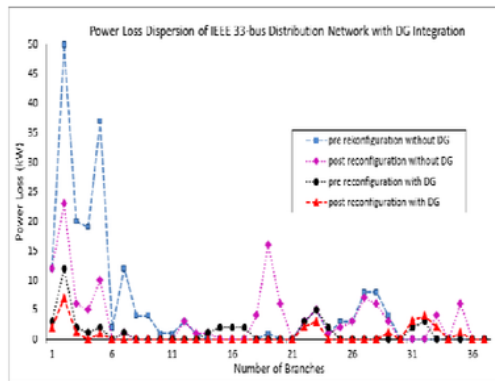


Figure 6. Power Loss Distribution Of IEEE 33-Bus Test System

Figure 6 shows the power loss distribution of IEEE 33-bus IEEE network test system in conditions of pre-reconfiguration without DG, post-reconfiguration without DG, pre-reconfiguration with DG, and post-reconfiguration with DG. It can be seen that the power losses magnitude on each branches is reduced by reconfiguration procedure. For example, on the branch 2, on pre-reconfiguration without DG configuration has 50 kW power losses but after configuration optimization decreased to 24 kW. The decrease is due to the network be reconfigured after the current flowing in the conductor 2 is smaller than the pre-reconfiguration of the radial network. Overall reduction of active power loss of the radial distribution network without the integration of DG for post-reconfiguration is 36.23%, which is decreased from 202.68 kW to 129.29 kW at post-reconfiguration. The optimal configuration of the radial network is obtained by making the status of

tie switches of 33, 35, and 36 to be closed while the sectionalizing switches of 6, 10, and 32 are open.

Integration of three DGs on the buses of 18, 22, and 33 with each capacity of 1.92 MW, 1.75 MW and 1.68 MW, respectively, has a significant impact on the reduction of power loss of IEEE 33 bus distribution network, as shown in Figure 6. For example in branch 2, on conditions of pre and post-reconfiguration of network without DG have power losses are 50 kW and 24 kW, respectively while after DG integration it has been plummeted to 12.5 kW. The decrease of power loss is due to the integration of DG on the buses 18, 22, and 33 accounted for active and reactive power in large enough so that the effect in increasing the overall magnitude of the bus voltage. Therefore, the current flowing in the conductor of distribution network is to be reduced. Total active power loss of distribution network is decreased from 202.64 kW to 43.51 kW. Furthermore, the optimal distribution network configuration further reduces power loss becomes 27.61 kW. The optimal distribution network configuration is obtained by making the status of tie switches 33, 35, and 37 be closed while the status of the sectionalizing switches 8, 19, and 27 to be open.

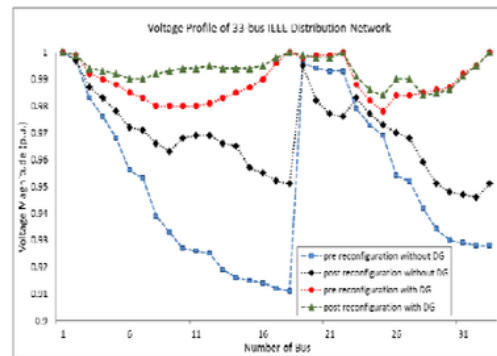


Figure 7. Voltage Profile Of IEEE 33-Bus Radial Network Test System

Figure 7 shows comparison of the voltage profile of 33-bus IEEE model in conditions of pre-reconfiguration without DG, post-reconfiguration without DG, pre-reconfiguration with DG, and post-reconfiguration with DG. In the test of network optimization without DG has resulted voltage profile improvement in almost all buses, except on buses 1, 20, 21, and 22. In the bus 1, voltage magnitudes remain in an ideal magnitude of 1 p.u. corresponding to a maximum of restraint in

this optimization. On buses of 20, 21, and 22, there were a slight decrease in voltage magnitude as a consequence of changes in the status of the current configuration switches. As can be seen in the results of configuration optimization in Figure 7, the buses of 20, 21, and 22 are connected to more buses, so they are resulting in a slight voltage drop. In overall, the voltage profile of post-reconfiguration condition is better than pre reconfiguration condition. The lowest voltage magnitude of pre-reconfiguration is 0.913 p.u. on bus of 18 while the lowest voltage magnitude of post-reconfiguration is 0.949 p.u. on the same bus, as shown in Figure 7.

Integration of three DGs on IEEE 33-bus distribution network model has a significant impact on bus voltage profile improvement. Figure 7 shows that the voltage magnitude for entire bus increases except bus 1 which has reached 1 p.u. The improved voltage profile can be seen from the increasing in magnitude of the lowest voltage magnitude. In condition without DG, the lowest voltage magnitude is 0.915 p.u. on bus of 18 while in condition with DG integration is 0.978 p.u. on bus 25 for the same network configuration, as shown in Figure 7. The increase is due to the integration of DG on the buses 18, 22, and 33 so the active and reactive power is large enough. Therefore, the impact increasing the overall magnitude of the bus voltage is obtained. In particular, it can be observed especially on the bus of 18. The voltage magnitude on bus of 18 is the lowest voltage in IEEE 33 bus power distribution network on the initial conditions, i.e. 0.914 p.u. Integration of DG1 with a capacity of 1.92 MW on bus 18 is adequate to increase the magnitude of the voltage to 1 p.u. Likewise with integration of DG3 with a capacity of 1.68 MW on bus 33 is adequate to raise the voltage magnitude from 0.929 to 1 p.u.

5. CONCLUSION

In this study, the clonal selection immune system algorithm was tested on an IEEE 33-bus distribution network. Based on the results, it was shown that the algorithm is effective in enhancing efficiency of the two test distribution systems. Efficiencies of the IEEE 33-bus distribution network in the pre reconfiguration without DG is 94.81%, post reconfiguration without DG is 96.61%, pre reconfiguration with DG is 98.82%, and post reconfiguration with DG is 99.23%. In order to see the performance of AIS algorithm, it has also been tested on the voltage profile for the IEEE 33-bus distribution network. The result of the

optimization is that the integration of DG in the test networks has obtained in improved voltage quality. The voltage quality is to be improved further by reconfiguring the distribution network.

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