Artificial Immunity Based Wound Healing Algorithm for Power Loss Optimization in Smart Grids

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***Abstract*—In this study, a human immune system based wound healing algorithm is mentioned to optimize power losses in the smart grids. The smart grids are a concept that uses communication and control techniques to increase the efficiency of today's electrical systems, provide bidirectional communication and allow instant monitoring of the grid. The wound healing algorithm is computationally simulated in the event of a possible injury to the human body and there are very few publications on the proposed algorithm when the literature review is performed. Therefore, the proposed algorithm is capable of removing this gap in the literature. The codes are written in the Matlab GUI environment and applied to the IEEE 30-busbar system and power losses are tried to be optimized. Simulation results show that the actual power loss is significantly reduced. The obtained results were compared with the results of other algorithms that are available in the literature. The proposed wound healing algorithm has given more optimum and superior solutions than the other algorithms compared in terms of calculation time and optimum power loss values and it was emphasized that it was a more effective method in providing the solution.**

***Index Terms*—smart grids, load flow, optimization methods, power system analysis computing, power system simulation.**

I. Introduction

The system consisting of production, transmission and distribution stations, providing uninterrupted and reliable electrical energy is called power system. Losses in power systems are a condition that is available in the transmission of energy from the generation of electrical energy to consumers. The electric power system consists of three subsystems: Generation, transmission, and distribution. Losses are greater as distribution systems use lower voltages than generation and transmission systems. Therefore, especially in recent years many types of research have been done on reducing the losses in the distribution system. Commonly used methods to reduce power losses in the distribution system are: Using a voltage regulator, adding capacitors to the grid, increasing the voltage in the grid, and restructuring the grid.

In recent years, many types of research and studies have focused on smart grids, a new model of electrical power systems. The main purpose of these studies is to make the electrical power systems to meet the current electricity needs without any problems in the production, transmission and distribution stages [1]. The smart grids allow the use of new control, increase the efficiency of existing power networks and use automated, computation and communication technologies for the control and monitoring of electrical power systems. For the electricity grid to achieve these, transmission, generation, and distribution infrastructures must be made compatible with communication, control, protection, and optimization technologies [2].

Smart grid technologies use information and communication technologies to transmit energy from the production center to consumers through bidirectional transmission and integrate distributed energy sources into the network to control and distribute energy. Thus it reduces the likelihood of a possible power outage spread to other parts of the grid and avoids losses of millions of dollars [3]. As a result, the reliability and efficiency of existing electrical systems are increased. Figure 1 shows the conceptual model of the smart grid.

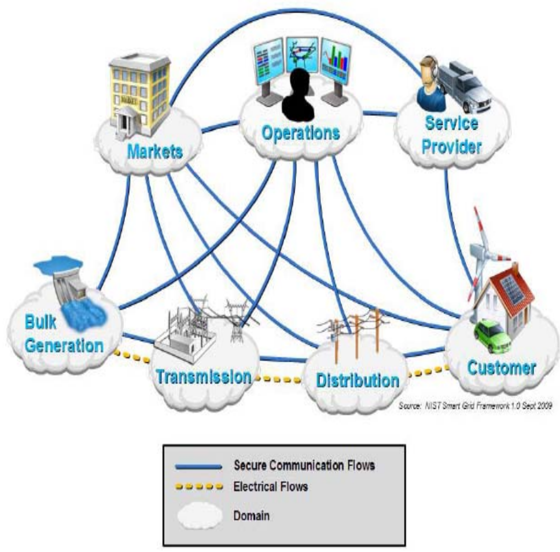

Figure 1. Conceptual model of smart grid [4]

The smart grids are expected to have the following characteristics:

a) Power quality
b) Self-healing
c) Ability to analyze information
d) Inclusion of consumers in the system

The gradual transformation of electrical power systems into smart grids is inevitable. To activate the decision-making mechanism in the event of a fault in the electrical power system, the values before the failure must be

Digital Object Identifier 10.4316/AECE.2020.01002

understood and analyzed. In such a case, this information can be accessed from the database in smart grids [5]. Optimization algorithms are used to minimize power loss in smart grids. The most commonly used bio-inspired optimization algorithms are artificial bee colony [6], ant colony [7], firefly [8], genetic algorithm [9], particle swarm algorithm [10] and artificial immune system algorithms. The studies to optimize power loss in the literature are given in Table I.

The artificial immune system based wound healing algorithm proposed in this study is computationally mimicking the human immune system. The human immune system is a system that protects the body from microscopic organisms that can harm the body. How does our body perceive when a foreign substance enters the body? Scientists regularly inject inactive cancer cells or proteins into a cancer patient, allowing the person's immune system to recognize and attack viable cancer cells. The human immune system is an adaptive system that recognizes and attacks the enemy.

In this article, an artificial immune system based wound healing algorithm that mimics the human wound healing process is mentioned. The solution stages of the algorithm and the flow diagram are given and codes are written in the Matlab GUI environment and applied to a current test system. In this article, the structure of the human immune system and the wound healing process are mentioned in the second part; the power optimization problem in the smart grid is discussed in detail in the third part; the wound healing algorithm was applied to a sample test system and the results were compared with other bio-inspired algorithms in the fourth part and the results were given in fifth part.

TABLE I. OPTIMUM POWER LOSS STUDIES IN THE LITERATURE

Reference	Using Algorithm	Objective	Power System
[11]	IEP	Power loss	IEEE 118-busbar system and a power system in China
[12]	MFO	Power loss,minimum voltage deviation	IEEE 30, IEEE 57, IEEE 118-busbar system
[13]	SA-PSO	Power loss and voltage stability	IEEE 14-busbar system
[14]	FAPSO	Power loss,voltage deviation and voltage stabiliy index	IEEE 30, IEEE 118-busbar system
[15]	ALO	Power loss	IEEE 30, IEEE 57, IEEE 300-busbar system
[16]	SOA	Power loss	IEEE 57, IEEE 118-busbar system
[17]	CLPSO	Power loss and voltage profile	IEEE 30, IEEE 118-busbar system
[18]	BBO	Power loss and voltage profile	IEEE 30, IEEE 118-busbar system
[19]	ABC	Power loss	IEEE 30, IEEE 118-busbar system
[20]	PSO	Power loss	IEEE 6-busbar system

IEP [11]: Improved hybrid evolutionary algorithm
MFO [12]: Moth-flame optimization
SA-PSO[13]: Simulated annealing particle swarm algorithm
FAPSO [14]: Fuzzy adaptive particle swarm
ALO [15]: Ant Lion optimization
SOA [16]: Seeker optimization algorithm
CLPSO [17]:Comprehensive learning particle swarm optimization
BBO [18]: Biogeography based optimization
ABC [19]: Artificial bee colony algorithm
PSO [20]: Particle swarm optimization

II. HUMAN IMMUNE SYSTEM

The B cells in the human body first learn to distinguish the enemies of the body from other cells before they begin to defend the body. Antibodies produced by B cells can identify enemies by looking directly at their shape without any outside help. The receptor on the antibody surfaces meets the antigen and binds to several small fragments of the antigen. Thus, with the help of receptors, B cells can easily recognize antigens such as bacteria [21].

A. The Function of B Cells

B cells are always responsible for protecting the body. When these cells encounter an attack from the outside, they begin to divide rapidly to produce antibodies. The produced antibodies catch germs and mark them as a foreign enemy cell. These marked enemy cells are expelled from the body by the intervention of phagocytes and T cells. Millions of antibodies produced by B cells not only neutralize enemies, but also marks enemies as lethal cells. The most important issue in these external attacks on the human body is to detect and destroy enemies. The amount of antibody to be produced is one of the major problems. There are fewer genes in the human body than the number of antibodies produced. Despite this negative situation, approximately one million antibodies are produced in half an hour. B cells have to make combinations with other genes to produce antibodies.

B. Antibodies

Antibodies are protective weapons produced by B cells to combat harmful cells entering the human body. There are two main tasks: First; to bind itself to harmful cells also known as antigens, second; to break down the biological structure of the antigen and make it disappear. One of the important features of the human body is to produce a compatible antibody for every enemy that attacks the body. From this point of view, it is concluded that antibodies are not uniform. Depending on the structure of the enemy, the externally attacked body produces antibodies that are strong enough to overcome. For each disease that will occur in our body, different structure of antibodies are produced. This is similar to the key-lock system. Cells in the human body combine about 100000 gene types in different combinations to produce antibody types. The appropriate antibody is produced by combining the information in different genes. Antibodies consist of two light and two heavy amino acid chains and hold together in the form of Y as shown in Figure 2.

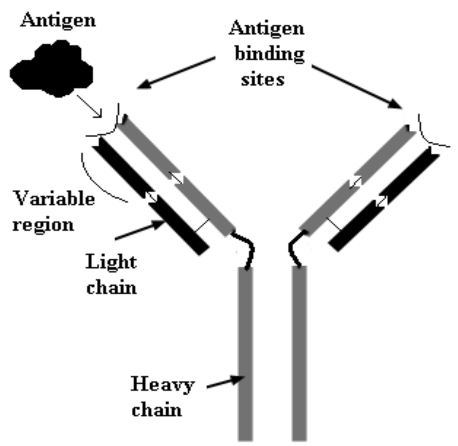

Figure 2. Antibody molecule [22]

III. Mathematical Model of Power Optimization Problem

Power optimization is the process of minimizing transmission line losses by distributing power optimally to all busbars in the system. The power optimization problem's mathematical model is described in detail below.

A. Objective Function

If power optimization is considered in operating conditions, the aim is to minimize line losses.
Power flow problem can be defined as:
Solve: *f(x,u)*
By using: *g(x,u)= 0* and *h(x,u)<0*
f and *g* symbolizes the objective function and the load flow equations as *h* shows the parameter limit.

$$x = \left[P_{Gslack} V_L Q_G S_l\right] \tag{1}$$

The parameter x shows the variables of slack bus power generation, load bus voltages, reactive power generation and line load.

$$u = \left[P_G V_G Q_C T\right] \tag{2}$$

u indicates system matrix variables including generator power, voltage, injected reactive power and tap changer transformers ratio. Power losses in the electric grid are expressed in equation (3):

$$P_{loss} = \sum_{i=1, j\in i}^{N} G_{ij}\,(V_i^2 + V_j^2 - 2.V_i.V_j.\cos\theta_{ij}) \tag{3}$$

N : Busbar total numbers
N_g: Number of busbars to which generators are connected
$G_{i,j}$:Mutual conductivity between busbars *i* and *j*
V_i: Amplitude of the busbar voltage *i*
V_j: Amplitude of the busbar voltage *j*
θ_{ij} :Phase angle between busbars *i* and *j*

B. Active and Reactive Power Constraints

$$P_{Gi} - P_{Li} = V_i \sum_{j=1}^{N} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \tag{4}$$

$$Q_{Gi} - Q_{Li} = V_i \sum_{j=1}^{N} V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \tag{5}$$

P_{Gi} : *i.th* busbar's active power value
Q_{Gi} : *i.th* busbar's reactive power value
P_{Li} : Active power loaded on the *i.th* busbar
Q_{Li} : Reactive power loaded on the *i.th* busbar
G_{ij} : Mutual conductivity between busbars *i* and *j*
B_{ij} : Susceptance between busbars *i* and *j*

C. Inequality Constraints

To ensure the system security of the elements in the smart grid, inequality constraints are used which indicate the upper and lower limits of the elements.

$$P_{gslack}^{\min} \le P_{gslack} \le P_{gslack}^{\max} \tag{6}$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{g,}^{\max}, i \in N_G \tag{7}$$

$$V_i^{\min} \le V_i \le V_{i,}^{\max}, i \in N \tag{8}$$

$$T_i^{\min} \le T_i \le T_{i,}^{\max}, i \in N_T \tag{9}$$

$$Q_c^{\min} \le Q_c \le Q_{c,}^{\max}, i \in N_C \tag{10}$$

N: Busbar total numbers
N_T*:* Transformer total numbers
N_C*:* Shunt reactive compensator total numbers
N_G*:* Generator total numbers
T_i*:* Shunt compensators' reactive power value

IV. Wound Healing Algorithm

The basic structure of the wound healing algorithm is based on the clonal selection principle. Figure 3 shows the proposed algorithm's flowchart. First, the initial population of P is produced. The selection process then selects n antibodies with the best affinity property to form a new P_n population. The basic rule in the selection process is the affinity value of the antibodies. Individuals in this population are cloned with the help of the cloning process to create a new population. Clone numbers depend on the affinity value of the antibodies. The clones are then mutated to form a new population using the hypermutation process. The basic rule in the mutation process is that antibodies with a high-affinity value have a lower mutation rate or clones with a low-affinity value have a higher mutation rate. Because antibodies close to the local optimum value are closer to the solution value, but antibodies that are far from the optimal solution, they undergo a large amount of mutation to move towards the optimal solution. The re-selection process checks whether the best clones are better than their families.

Finally, with the help of the metadynamics process, low similar antibodies are replaced by new antibodies. Selection, cloning, and maturation move the population towards the best solution.

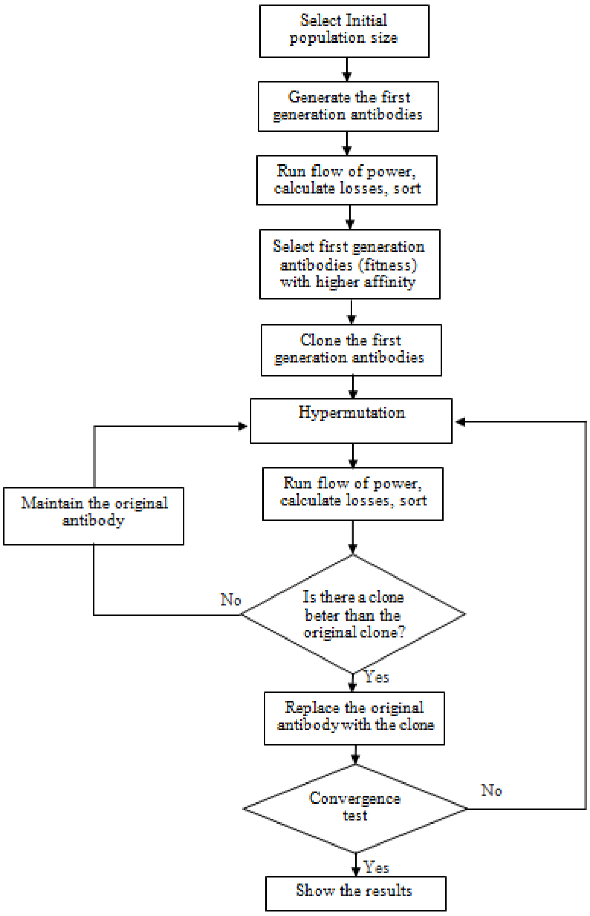

Figure 3. The flowchart of wound healing algorithm

A. Wound Healing Algorithm Solution Stages

1. Generate the initial population *(P)* with *N* antibodies.
2. Determine affinity for each antibody in the *P* population. Select *n* antibodies with the best affinity *(N_s)* and generate the P_n population. The affinity value between antibody and antigen is calculated by equation (11):

$$d = \sum_{i=1}^{N} (Ag_i - Ab_i)^2 \quad (11)$$

The calculated threshold value *d* is compared with *λ* and the *E* marking error is calculated as follows:

$$E = d - \lambda \quad (12)$$

If $E > 0$, the antibody does not recognize the antigen and there is no affinity between them. If the *E* value is between 0 and 1, there is an affinity between them.

3. Clon the n antibodies selected in step 2 and create temporary clone population N_c. Equation (13) is used to form N_c.

$$Nc_i = round\left(\frac{\alpha * N_s * f}{i}\right) \quad (13)$$

α :Cloning coefficient (value ranges from 0 to 1)
f: Cloning acceleration factor (value range from 0.9 to 0.99)
N_s: Best number of antibodies selected in step 2.

4. Hypermutate the N_c clone population. Build the subpopulation N_c^*. Hypermutation is proportional to the affinity value of antibodies [23].
5. Calculate the affinity value of each antibody of the N_c^* subpopulation and select the antibodies with the best value from which to generate $N_{c(n)}^*$ and add to the initial population.
6. Replace antibodies with low affinity values by new antibodies.
7. If the value of the *P* population is less than *N*, produce antibodies to complete the population.
8. Converge your test. If the test is successful, stop the program. Otherwise, continue the process.

B. Application of the Algorithm to the Power Loss Optimization Problem

1. step: Create the initial population
In the initial step, the antibody population is generated randomly from real-coded numbers. In the power loss optimization problem, the generator's actual power values, generator voltages and reactive power values in the busbars are generated as antibodies.

2. step: Determine the affinity value of each antibody
The suitability value of the wound healing algorithm is considered to be the total power losses of the smart grid. Total power losses in the network are obtained from the solution of the power flow problem by appropriate methods. Limit values are taken into consideration during the solution phase.

3. step: Cloning process
Total power losses in the distribution system are subjected to cloning.

4. step: Mutation process
The antibodies cloned in the previous step are mutated. The power flow problem determines the number of mutation processes.

5. step: Convergence test

$$\text{maximum}_{\text{fitness}} - \text{minimum}_{\text{fitness}} \leq 0.0001 \quad (14)$$

According to the convergence criterion in equation (14), it is determined whether the algorithm will continue to work or not. The algorithm continues to run until this condition occurs.

C. Introduction of the Test System

The test system to which the algorithm will be applied is the IEEE 30-busbar system (Figure 4). The general characteristics of the test system are taken from [25]. The test system has 41 lines, 6 generators at bus 1, 2, 5, 8, 11, 13 and 4 transformers with off-nominal tap ratio at lines 6-9, 6-10, 4-12, 28-27. In addition, there are 9 shunt VAR compensation devices connected to bus 10, 12, 15, 17, 20, 21, 23, 24 and 29 that can be controlled within the constraints. The initial values of the IEEE 30-busbar system are given in Table II.

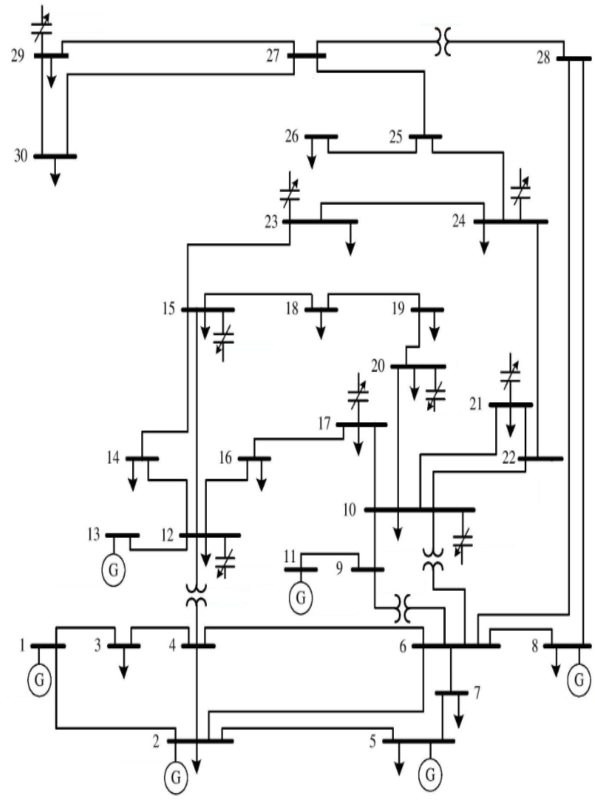

Figure 4. IEEE 30-busbar system

TABLE II. INTRODUCTION OF IEEE 30-BUSBAR SYSTEM

Busbar total numbers		30		
Line total numbers		41		
Generator total numbers		6		
Tap changing transformer total numbers		4		
Shunt capacitor total numbers		9		
Load busbar total numbers		24		
Active power loss' initial value (MW)		5.811		
Reactive power loss' initial value (MVAR)		32.417		
Various variables' limits				
	Voltage of generators (p.u)	**Transformer tap ratio (p.u)**	**Capacitor banks (MVAR)**	**Load voltage (p.u)**
Min	0.95	0.9	0	0.95
Max	1.1	1.1	5	1.05

D. Optimizing Power Loss for IEEE 30-Busbar System

Table III presents the parameters and values used in the proposed wound healing algorithm. Unlike the existing artificial immune system algorithms in the literature, f (clone acceleration factor) was added. The reason for the addition of clone acceleration factor is to provide faster and more robust results. In solution 3 of the algorithm, the temporary clone population was added to equation (13) to obtain N_c, so that the solution was faster. One of the most important steps of the algorithm is to create a temporary clone population. In the next step, the number of antibodies to be subjected to hypermutation will vary. This will make the solution faster, more accurate and optimized. Table III shows the values of the parameters used in the algorithm for the best solution. When α (cloning coefficient): 0.9, f (clone acceleration factor): 0.92 is taken, the most optimized results were obtained. The change in power loss due to these values is given in Table IV.

TABLE III. PARAMETERS USED IN THE WOUND HEALING ALGORITHM (THE BEST SOLUTION)

Parameter	Value
Population number	100
Maximum iteration	100
Number of runs	100
Cloning coefficient *(α)*	0.9
Clon acceleration factor *(f)*	0.92

TABLE IV. OPTIMUM POWER LOSS VALUES ACCORDING TO WOUND HEALING ALGORITHM PARAMETERS

Number of population	25	50	**100**	100	100
Number of iteration	25	50	**100**	100	100
Number of runs	100	100	**100**	100	100
α (cloning coefficient)	0.6	0.6	**0.9**	0.9	0.95
f (clon acceleration factor)	0.6	0.8	**0.92**	0.95	0.99
P_{loss} (MW)	4.6408	4.5504	**4.4709**	4.5112	4.5345

The optimum power loss value obtained as a result of the proposed algorithm according to the number of iterations is shown in Figure 5. The graph is obtained by using the number of population: 100, number of iterations: 100, α (cloning coefficient): 0.9, f (clone acceleration factor): 0.92. The value obtained as a result of the algorithm was calculated as 0.044709 in per unit and is the best optimum value.

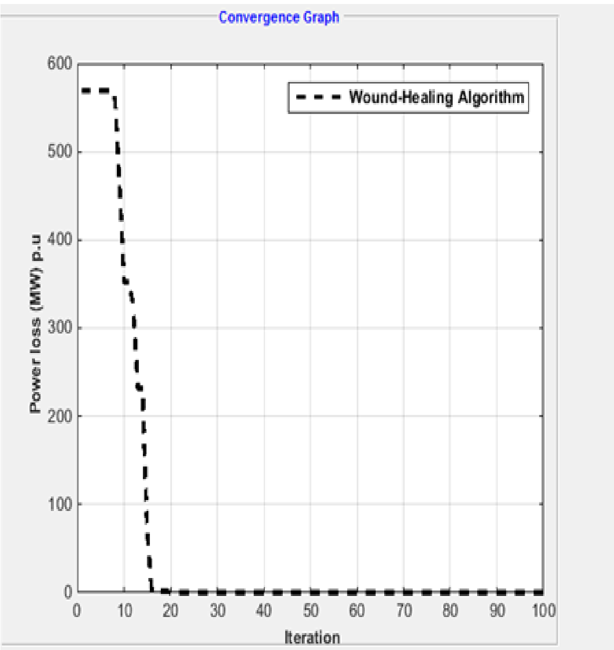

Figure 5. Graph of change of optimum power loss according to iteration number

TABLE V. OPTIMIZATION RESULTS OF THE IEEE 30-BUSBAR SYSTEM (BUSBAR VOLTAGES)

Busbar no	Voltage's initial values p.u	Voltage values (obtained as a result of wound-healing algorithm) p.u	Busbar no	Voltage's initial values p.u	Voltage values (obtained as a result of wound-healing algorithm) p.u
1	1.0228	1.1000	16	1.0599	0.9708
2	1.0622	1.0695	17	1.0585	0.9762
3	1.0411	1.0500	18	1.0450	0.9581
4	1.0449	1.0387	19	1.0440	0.9587
5	1.0953	1.0339	20	1.0488	0.9649
6	1.0503	1.0277	21	1.0515	0.9738
7	1.0605	1.0226	22	1.0513	0.9745
8	1.0646	1.0317	23	1.0404	0.9588
9	1.0917	1.0350	24	1.0305	0.9629
10	1.0651	0.9867	25	1.0056	0.9769
11	1.0850	1.0226	26	0.9877	0.9584
12	1.0686	0.9733	27	0.9990	0.9948
13	1.0850	0.9500	28	1.0504	1.0249
14	1.0557	0.9630	29	0.9826	0.9895
15	1.0520	0.9627	30	0.9692	1.0188

The initial voltage values of the IEEE 30-busbar test system and the optimum voltage values obtained by wound healing algorithm are shown in Table V. When the voltage values in Table V are examined, it is seen that the busbar voltages obtained are between the optimum voltage values (0.95 p.u ≤ V_{busbar} ≤ 1.1 p.u). The comparison of the initial and the optimum voltage values are given in Figure 6. Optimum results were obtained by using Table III values.

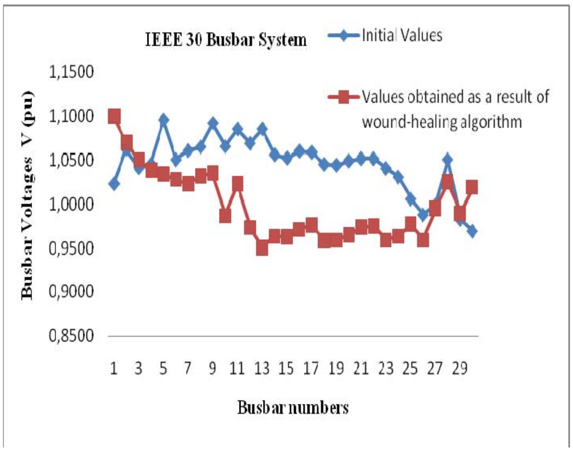

Figure 6. Values obtained as a result of wound healing algorithm with initial values (Busbar voltages)

Table VI shows the statistical analysis of the proposed and compared algorithms. All algorithms were run 100 times to compare the best, worst and mean values, standard deviation and simulation time. Since the algorithms are stochastic, the single operation does not make sense. Therefore, the algorithms were run 100 times during the comparison and the obtained results are given in Table VI. It is clearly shown in Table VI that the proposed wound healing algorithm gave at the best value, standard deviationand simulation time better results than other algorithms. These results show the superiority of the algorithm.

TABLE VI. STATISTICAL ANALYSIS OF ALGORITHM (100 TRIAL RUNS)

Algorithm	Best value (MW)	Worst value (MW)	Mean value (MW)	Standard deviation	Simulation time (Sec.)
DE [24]	NR*	NR*	NR*	NR*	NR*
GSA [25]	NR*	NR*	NR*	NR*	NR*
BBO [26]	4.5511	4.5522	4.551	NR*	110
PSO [27]	4.6282	4.7986	4.736	0.0011	130
CLPSO [27]	4.5615	4.6833	4.639	0.0007	138
WHA (Proposed algorithm)	**4.4709**	4.6626	4.534	0.00064	104

NR*: means not reported

One of the important parameters in the proposed wound healing algorithm is the population number. Other parameters used in the algorithm (number of iterations, number of runs, α cloning coefficient, f clone acceleration factor) are kept constant and optimum power loss values according to population number are given in the Table VII.

TABLE VII. OPTIMUM P_{LOSS} VALUES ACCORDING TO POPULATION NUMBER

Number of population	25	50	75	100	150	200
Number of iteration	100	100	100	100	100	100
Number of runs	100	100	100	100	100	100
α (coefficient of cloning)	0.9	0.9	0.9	0.9	0.9	0.9
f (clon acceleration factor)	0.92	0.92	0.92	0.92	0.92	0.92
P_{loss} (MW)	4.715	4.630	4.575	**4.47**	4.554	4.586

When the Table VII is examined, if the number of population continues to increase after a certain value, the optimum power loss value increases. The proposed algorithm is sensitive to change in parameters. Similar works can be done for other parameters. Since the proposed algorithm is stochastic, the number of runs should be kept at least 30. Because the algorithm takes the first values randomly while running, the program will give different results in each run.

TABLE VIII. EFFECT OF REACTIVE POWER CHANGE ON SIMULATION TIME (100 TRIAL RUNS)

Number of population	100	100	100	100	100
Number of iteration	100	100	100	100	100
Number of runs	100	100	100	100	100
α (cloning coefficient)	0.9	0.9	0.9	0.9	0.9
f (clon acceleration factor)	0.92	0.92	0.92	0.92	0.92
Q (reactive power increase rate) %	0	10	25	40	50
Simulation time(second)	104	108	114	119	126
P_{loss} (MW)	4.4709	4.4914	4.5258	4.5484	4.5649

In particular, the active and reactive power values available in the test systems can be increased in certain proportions according to the equality and inequality constraints specified in section three. The initial values of the algorithm can be increased by up to 50% in the program written in the Matlab GUI environment. This ratio is sufficient because the current values of the generators, compensators, and transformers in the system should not be increased randomly to prevent physical stress. Table VIII shows the response time of the program and the P_{loss} values obtained according to the percentage increase in reactive power. The number of population, number of iterations, number of runs, clone coefficient and clone acceleration coefficient values used in the creation of Table VIII are the values used to obtain the optimum P_{loss} value. When Table VIII is examined, the % increase in reactive power affects the simulation and P_{loss} values in a small amount. For example, when 50% increase in reactive power is achieved, the P_{loss} value increases from 4.4709 to 4.5649 and the simulation time increases from 104 seconds to 126 seconds. The increment amounts are very small. These results prove that the algorithm is robust and superior.

In Table IX, the proposed algorithm results are compared with other current optimization algorithms with the same conditions and the same number of runs. When Table IX is examined, it is seen that the proposed algorithm gave the best solution.

TABLE IX. COMPARISON OF SIMULATION RESULTS FOR IEEE-30 BUSBAR SYSTEM WITH P_{LOSS} MINIMIZATION OBJECTIVE

Control variables	**WHA (Proposed algorithm)**	**OGSA [28]**	**DE [24]**	**GSA [25]**	**BBO [26]**	**PSO[27]**	**CLPSO [27]**
Generator voltage (p.u)							
V_1	1.1000	1.0500	1.1000	1.0716	1.1000	1.1000	1.1000
V_2	1.0695	1.0410	1.0931	1.0221	1.0944	1.1000	1.1000
V_5	1.0339	1.0154	1.0736	1.0400	1.0749	1.0867	1.0795
V_8	1.0317	1.0267	1.0756	1.0507	1.0768	1.1000	1.1000
V_{11}	1.0226	1.0082	1.1000	0.9771	1.0990	1.1000	1.1000
V_{13}	0.9500	1.0500	1.1000	0.9676	1.0990	1.1000	1.1000
Transformer tap ratio (p.u)							
T_{6-9}	0.9000	1.0585	1.0465	1.0984	1.0435	0.9587	0.9154
T_{6-10}	1.1000	0.9089	0.9097	0.9824	0.9011	1.0543	0.9000
T_{4-12}	1,0237	1.0141	0.9867	1.0959	0.9824	1.0024	0.9000
T_{28-27}	1,0075	1.0182	0.9689	1.0593	0.9691	0.9755	0.9397
Capacitor banks (MVar)							
Q_{c-10}	0.0000	3.3000	5.0000	1.6537	4.9998	4.2803	4.9265
Q_{c-12}	5.0000	2.4900	5.0000	4.3722	4.9870	5.0000	5.0000
Q_{c-15}	4.0766	1.7700	5.0000	0.1199	4.9906	3.0288	5.0000
Q_{c-17}	0.0000	5.0000	5.0000	2.0876	4.9970	4.0365	5.0000
Q_{c-20}	0.0000	3.3400	4.4060	0.3577	4.9901	2.6697	5.0000
Q_{c-21}	0.0000	4.0300	5.0000	0.2602	4.9946	3.8894	5.0000
Q_{c-23}	0.0000	2.6900	2.8004	0.0000	3.8753	0.0000	5.0000
Q_{c-24}	3.0756	5.0000	5.0000	1.3839	4.9867	3.5879	5.0000
Q_{c-29}	5.0000	1.9400	2.5979	0.0003	2.9098	2.8415	5.0000
P_{loss} (MW)	**4.4709**	4.4984	4.5550	4.5143	4.5511	4.6282	4.5615

WHA (Proposed algorithm): Wound-healing algorithm
OGSA[28]: Opposition-based gravitational search algorithm
DE [24]: Differential evolution algorithm
GSA [25]: Gravitational search algorithm
BBO [26]: Biogeography-based optimization

When Table II is analyzed, the power loss before the optimization process is 5.811 MW. The optimal values of the control variables were obtained from the program written in Matlab GUI and the values are given in Table IX. The proposed algorithm's results were compared with DE, GSA, BBO, PSO, CLPSO and OGSA algorithms. The results of the compared algorithms were obtained from the relevant references. The best-optimized power loss (P_{loss}) value calculated in wound healing algorithm is 4.4709 MW.

Among the algorithms given in Table IX, the OGSA algorithm's value of P_{loss} is 4.4984 and is the best value. The result of the proposed algorithm is 0.0275 MW better than this value and smart grid optimization has been achieved with 0.611% less power loss. The initial power loss of the IEEE 30-busbar system was 5.811 MW, which decreased to 4.4709 MW as a result of the wound healing algorithm. The power loss value decreased by 1.3401 MW and 23.06%.

V. CONCLUSION

Power loss in smart grids is one of the factors affecting system performance and reliability. While performing the optimum power loss analysis, the equilibrium and inequality constraints of the smart grid are formulated as a nonlinear optimization problem. In this study, an artificial immune system based wound healing algorithm is mentioned. It has been shown that the proposed algorithm can provide optimum settings of control variables in smart grids. The program was written in the Matlab GUI environment and applied to the IEEE 30-busbar system and compared with other algorithm results as shown in Table IX. Simulation results show that the proposed algorithm is robust and superior. When the literature reviews are performed, it is seen that there are very few publications about the algorithm that computationally simulates the human wound healing process. The proposed algorithm is capable of filling this gap in the literature. Standard deviation and simulation time are less than other compared algorithms. Therefore, the algorithm can be proposed as a promising method to solve other optimization problems in the smart grids (optimum fuel cost, voltage profile improvement, etc.). In future studies, the algorithm will be applied to different IEEE-busbar test systems and robustness and superiority will be investigated for different optimization problems.

REFERENCES

[1] J. Dongli, X. Meng and X. Song, “Study on technology system of self-healing control in smart distribution grid,“ International Conference on Advanced Power System Automation and Protection, Beijing, 2011, pp.26-30. doi: 10.1109/APAP.2011.6180379

[2] X. Fang, S. Misra, G. Xue and D.Yang, ”Smart grid-the new and improveds power gird: a survey”, IEEE Communication Surveys& Tutorials, vol. 14, no. 4, pp. 944-980, 2012. doi:10.1109/surv.2011.101911.00087

[3] M.Çınar and A. Kaygusuz, "Optimum Fuel Cost in Load Flow Analysis of Smart Grid by Using Artificial Bee Colony Algorithm," International Artificial Intelligence and Data Processing Symposium (IDAP), Malatya, Turkey, 2019, pp. 1-5. doi: 10.1109/IDAP.2019.8875893

[4] NIST, NIST framework and roadmap for smart grid interoperability standards, Release 3.0, 2014.

[5] R. P. Guerrero, G. T. Heydt, N. J. Jack, B. K. Keel and A. R. Castelhano, "Optimal Restoration of Distribution Systems Using Dynamic Programming," IEEE Transactions on Power Delivery, vol. 23, no. 3, pp. 1589-1596, 2008. doi: 10.1109/TPWRD.2007.916112

[6] A survey: Algorithms stimulating bee swarm intelligence (Karaboğa,Akay,2009).

[7] T. Q. D. Khao and B.T.T. Phan, ”Ant colony search-based loss minimum for reconfiguration of distributed systems,” IEEE Power India Conference New Delphi, India, 2006, pp.1-6. doi: 10.1109/POWERI.2006.1632571

[8] X.S.Yong and X.He, ”Firefly algorithm: Recent advances and applications,” International Journal of Swarm Intelligence, vol. 1, pp. 36, 2013. doi: 10.1504/IJSI.2013.055801

[9] J. C. Cebrian and N. Kagan, “Reconfiguration of distribution networks to minimize loss and disruption costs using genetic algorithms,” Electric Power Systems Research, vol. 80, no. 1, pp. 53-62, 2010. doi:10.1016/j.epsr.2009.08.005

[10] B. Zhao, C. X. Guo and Y. J. Cao, "A multiagent-based particle swarm optimization approach for optimal reactive power dispatch," IEEE Transactions on Power Systems, vol. 20, no. 2, pp. 1070-1078, 2005. doi: 10.1109/TPWRS.2005.846064

[11] W. Yan, S. Lu and D. C. Yu, “A novel optimal reactive power dispatch method based on an improved hybrid evolutionary programming technique,” IEEE Transactions on Power Systems, vol. 19, no. 2, pp. 913–918, 2004. doi: 10.1109/tpwrs.2004.826716

[12] R. N. S. Mei, M. H. Sulaiman, Z. Mustaffa and H. Daniyal, “Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique,” Applied Soft Computing, vol. 59, pp. 210-222, 2017. doi:10.1016/j.asoc.2017.05.057

[13] Y. Mao and M. Li, “Optimal reactive power planning based on simulated annealing particle swarm algorithm considering static voltage stability,” International Conference on Intelligent Computation Technology and Automation (ICICTA),Hunan, 2018, pp.106–110. doi: 10.1109/ICICTA.2008.427

[14] Z. Wen and L. Yutian, “Multi-objective reactive power and voltage control based on fuzzy optimization strategy and fuzzy adaptive particle swarm,” Electric Power and Energy Systems, vol. 30, no. 9, pp. 525–532, 2008. doi:10.1016/j.ijepes.2008.04.005

[15] S. Mouassa, T. Bouktir and A. Salhi, “Ant lion optimizer for solving optimal reactive power dispatch problem in power systems,” Engineering Science and Technology an International Journal, vol. 20, no. 3, pp. 885-895, 2017. doi:10.1016/j.jestch.2017.03.006

[16] D. Chaohua, C. Weirong, Z. Yunfang and Z. Xuexia, ”Seeker optimization algorithm for optimal reactive power dispatch,” IEEE Transactions on Power Systems, vol. 24, no. 3, pp. 1218–1231, 2009. doi:10.1109/TPWRS.2009.2021226

[17] K. Mahadevan and P.S. Kannan, “Comprehensive learning particle swarm optimization for reactive power dispatch,” Applied Soft Computing, vol. 10, no. 2, pp. 641–652, 2010. doi:10.1016/j.asoc.2009.08.038

[18] P. K. Roy, S. P. Ghoshal and S. S. Thakur, “Optimal VAR control for improvements in voltage profiles and for real power loss minimization using biogeography based optimization,” Electric Power and Energy Systems, vol. 43, no. 1, pp. 830–838, 2012. doi:10.1016/j.ijepes.2012.05.032

[19] K. Ayan and U. Kılıc, “Artificial bee colony algorithm solution for optimal reactive power flow,” Applied Soft Computing, vol. 12, no. 5, pp. 1477–1482, 2012. doi:10.1016/j.asoc.2012.01.006

[20] A. Q. Badar, B. S. Umre and A. S. Junghare, “Reactive power control using dynamic particle swarm optimization for real power loss minimization,” Electric Power and Energy Systems, vol. 41, no. 1, pp. 133–136, 2012. doi:10.1016/j.ijepes.2012.03.030

[21] L.N. de Castro and J.Timmis, “Artificial Immune Systems: A New Computational Intelligence Approach," Springer-Verlag,2002.

[22] R. Belkacemi and A. Feliachi, "An immune system approach for power system automation and self healing," 2009 IEEE/PES Power Systems Conference and Exposition, Seattle, WA, 2009, pp. 1-7, doi: 10.1109/PSCE.2009.4840209

[23] S. S. F. Souza, R. Romero and J. F. Franco, “Artificial immune networks Copt-aiNet and Opt-aiNet applied to the reconfiguration problem of radial electrical distribution systems,” Electric Power Systems Research, vol. 119, pp. 304-312, 2015. doi:10.1016/j.epsr.2014.10.012

[24] A. A. Abou El Ela, M. A. Abido and S. R. Spea, ”Differential evolution algorithm for optimal reactive power dispatch,” Electric Power Systems Research, vol. 81, no. 2, pp. 458–64, 2011. doi:10.1016/j.epsr.2010.10.005

[25] S. Duman, Y. Sonmez, U. Guvenc and N. Yorukeren, “Optimal reactive power dispatch using a gravitational search algorithm,” IET Generation, Transmission & Distribution, vol. 6, no. 6, pp. 563–576, 2012. doi:10.1049/iet-gtd.2011.0681

[26] A. Bhattacharya and P. K. Chattopadhyay, “Solution of optimal reactive power flow using biogeography-based optimization,” International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering, vol. 4, no. 3, pp. 621–629, 2010.

[27] K. Mahadevan and P. S. Kannan, “Comprehensive learning particle swarm optimization for reactive power dispatch,” Applied Soft Computing, vol. 10, pp. 641–652, 2010. doi:10.1016/j.asoc.2009.08.038

[28] B. Shaw, V. Mukherjee and S. P. Ghoshal, ”Solution of reactive power dispatch of power systems by an opposition-based gravitational search algorithm,” Electrical Power and Energy Systems, vol. 55, pp. 29–40, 2014. doi:10.1016/j.ijepes.2013.08.010