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DISTRIBUTION SYSTEMS OPTIMIZATION WITH COMPUTATIONAL INTELLIGENCE ALGORITHMS

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Abstract: A dual particle swarm optimization - immune algorithm solution is presented in this paper to deal with the problem of optimum radial reconfiguration and reactive power compensation in distribution systems. The optimization problem uses as minimization function power losses in the distribution system – lines and transformers – and addresses constraints referring lower and upper voltage limits, nodal reactive power limits, topology supply constraints and the maximum number of capacitor banks. The analysis conducted for a pilot and a complex test system has proven the feasibility of the proposed method.

Keywords: Capacitor placement, distribution systems, immune algorithm, particle swarm optimization, reactive power compensation, reconfiguration of open-loop systems.

1. INTRODUCTION

In distribution systems, power and energy losses are widely used as a basic criterion in optimization problems. Power or energy losses are also a direct expression of DISCO’s efficiency, being an important source for electricity and financial savings. At present, if DISCOs have not a firm control over network losses, electricity price volatility induced by unpredictable market behavior may seriously injure the financial balance of the company. In these circumstances, the development of new, intelligent tools, easy to implement and able to efficiently approach the problem of reducing power or energy losses in distribution systems is of great importance.

At present, due to more simple and efficient design and operational conditions, the most frequently applied solution uses a close-loop structure of the network, with open-loop operation. The open-loop operating structure of the network is obtained by opening certain switches in certain points, known as sectionalizing switches. Different sectionalizing switches produce different operating conditions and different values for the power or energy losses. Thus, one type of optimization problem, known as the system loss minimum reconfiguration, is to find the sectionalizing switches, which minimizes the power or energy losses in the distribution system.

Traditional methods were based on heuristic approaches (Glamocanin and Filipovic, 1993; Cannas, *et al.*, 1999.) and different search techniques (Glamocanin, 1990). Recent papers apply new technologies, like fuzzy logic (Skok, *et al.*, 2006), tabu search (Nara, *et al.*, 2002) or genetic algorithm (GA) (Filipec, *et al*., 1999). The fuzzy logic approach is well fitted especially when dealing with uncertain data, such as load data. Tabu search was applied in the conjunction with distributed generation, and was found to be an accurate approach only for small values for the number of sources. For large networks the combinatorial nature of GAs turns this method into a computationally expensive one.

On the other hand, reactive power compensation using capacitors installed in the nodes of the network is a widely used method for power loss reduction in distribution systems. This method has also positive effects over the general level of the voltage in the network, enhances the network operating conditions and increases the system capacity.

Capacitor placement problem for reactive power compensation has been approached using a wide

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range of computational methods. Traditional methods, based on analytical models, dynamic programming or gradient descent search procedures were applied in the early works (Baran and Wu, 1989).

More recent approaches use components of intelligent technologies like simulated annealing (Al-Mohammed and Elamin, ????), neural networks (Dash, *et al.*, 1991), fuzzy logic (De Souza, *et al.*, 2004) or genetic algorithms (Santos, *et al.*, 2004). Simulated annealing, a general-purpose stochastic optimization technique suffers occasionally of a too large computational time. Neural networks, which act as high performance approximants, may be used as optimizers especially for problems with not too high dimensions. Fuzzy logic can be used to represent uncertain information and to embed it in decision-making models. Genetic algorithms are a parallel search method inspired from natural selection mechanisms and were successfully applied to many similar optimization problems.

In this paper a new approach to the problem of optimization in distribution systems is proposed. This approach divides the problem into two subproblems and solves them sequentially. The first subproblem aims to identify the optimal open-loop configuration of the system and is approached using the Particle Swarm Optimization (PSO) technique. The second subproblem deals with the reactive power compensation and consists in finding the optimal placement of capacitors in the nodes of the radial network, and is approached using the Immune Algorithm (IA) technique. Both subproblems use power losses as optimization criterion.

PSO is an evolutionary computation technique, proposed for the first time in 1995 (Kennedy and Eberhardt, 1995), which emulate the "swarming" behavior of animals such as birds or insects. PSO is an algorithm for finding optimal regions in complex search spaces base on the cooperation / interaction of individuals in a "swarm" or "population of particles". This technique share many similarities with evolutionary computation techniques, such as GAs, but has no evolution operators. In PSO the potential solutions are initialized at random and the search goes for a global optimum by updating the particles flight through local optima. In power systems, PSO has been applied in problems like reactive power and voltage control, optimal power flow or state estimation (Yoshida, *et al.*, 2000; Abido, 2002; Naka, *et al*., 2003).

Since the middle of 1990s, Immune Algorithm (IA) or Artificial Immune System (AIS) have been successfully applied to a wide variety of domain, such as pattern recognition, data analysis, optimization, robotics, or computer security (De Castro, 2003). AIS and IAs were inspired from immunity mechanisms specific to living organisms, which protect them against bacteria, viruses and other microorganisms. Specific to these mechanisms are complex processes of genes recombination and antibodies reduction to cope with antigens invading the organism. In the field of power systems AISs were applied for optimization problems such as optimal post-fault reconfiguration of distribution systems, voltage control and coordination, short-term unit commitment problem or scheduling of cogeneration plants (Li, *et al.*, 2006; Liao and Tsao, 2004; Chen, *et al*., 2005).

2. PROBLEM FORMULATION

In a general description, the optimization problem addressed in this paper aims to determine an optimal radial structure of a distribution system and a combination of location, type and size of capacitors to be installed in the same system so that an objective function is minimized or maximized.

Most electric distribution systems are designed in a closed-loop topology but operate in a radial configuration. Opening or closing several switches from the system determines a change in its topology. In the open-loop radial distribution system, each radial feeder is divided into load sections with sectionalizing switches and has connections to other feeders via several other open switches. For each configuration a certain value of power and energy losses in distribution feeders will result. The minimum power loss reconfiguration problem consists in deciding the position of open switches, which best minimize distribution losses under certain constraints.

For the second optimization problem, in most cases, distribution systems operate at medium (MV) or low voltage (LV) and compensation of reactive power is done by installing capacitors on the MV or LV busbar of transformers. In this paper authors have considered the second case, when the capacitors are installed on the LV part of the transformer. This solution has the advantage that for a fixed number of installed capacitors, the reactive power flows lower not only in the MV network, but also through the transformer.

Because power or energy losses are critical components in the energy and / or financial balance of a DISCO, the objective of the optimization problem is to minimize power or energy losses while maintaining other parameters inside certain limits. In this paper, for simplicity, the case of power loss minimization was considered. Hence, the system loss minimum reconfiguration and the reactive power compensation and capacitor placement problems can be formulated as:

$$(1)\quad Min\left(\Delta P_{network}\right) = Min\left(\sum_{l=1}^{NL}\Delta P_l^{Line} + \sum_{t=1}^{NT}\Delta P_t^{Transf}\right)$$

subject to voltage, line capacity, topology structure or capacitor constraints:

$$(2)\quad V_t^{\min} \le V_t \le V_t^{\max} \qquad t = 1,\dots,\ NT$$

$$(3)\quad I_{l,1} \le I_{\max\ adm} \qquad l = 1,\dots,\ NL$$

$$(4)\quad \sum_i \alpha_{ij} = 1$$

$$(5)\quad N_t \cdot \Delta Q_K \le Q_t^{\max} \qquad t = 1,\dots,\ NT$$

$$(6)\quad \sum_{t=1}^{NT} N_t \le K_T$$

where: ΔP_l^{Line} – power loss in line l; ΔP_t^{Transf} – power loss in transformer t; NL and NT – number of power lines and transformers in the distribution system; $\Delta P_{network}$ – power loss in the entire network; V_t – voltage on the MV or LV part of transformer t; V_t^{max}, V_t^{min} – maximum / minimum allowable voltage on the MV or LV part of transformer t; $I_{l,1}$ – current on the first line section of feeder l; $I_{max\ adm}$ – maximum admissible current; N_t – number of capacitors installed on the MV or LV bus of transformer t; Q_t^{max} – maximum reactive power supplied to the consumer from node t; ΔQ_K – rated power of capacitors; K_T – total number of capacitors that can be installed in the system; α_{ij} – topology index (α_{ij} = 1 if line section j belongs to feeder I; α_{ij} = 0 otherwise).

For each combination of capacitors in the LV nodes of the systems, power losses are computed using a simple power flow procedure in the radial distribution system.

3. PARTICLE SWARM OPTIMIZATION MODEL

PSO is an evolutionary computation technique, which emulates the "swarming" behavior of animals such as birds or insects. Basically, PSO develops a population of particles that move in the search space through cooperation or interaction of individual particles. This technique share many similarities with evolutionary computation techniques, such as GAs, but has no evolution operators, like crossover or mutation. In PSO the potential solutions are initialized at random and the search goes for a global optimum by updating the particles flight through local optima. At any moment t, the position $X_p(t)$ of a particle p is computed based on its prior position $X_p(t-1)$ at moment $t-1$ and correction term called *velocity* $V_p(t)$. In its turn, the velocity assigned to each particle is computed using three components: (*i*) the influence of the previous value of velocity $V_p(t-1)$ or the history of the particle; (*ii*) the influence of the best personal solution for particle p, $XL_p(t)$ or the local optimum and (*iii*) the influence of the best solution so far for the entire population $XG(t)$ or the global optimum. These components are taken into consideration using three weighting factors, denoted by w_1, w_2 and w_3. The movement of the particles is described by equations:

$$(7)\quad \begin{aligned} &V_p(t) = w_1 \cdot V_p(t-1) + \\ &+ w_2 \cdot [XL_p(t) - X_p(t)] + w_3 \cdot [XG(t) - X_p(t)] \\ &X_p(t) = X_p(t-1) + V_p(t) \end{aligned}$$

In their turn, weighting factors w_i are computed on different basis. The weighting factor w_1 has a continuous dynamic, lowering during the iterative process:

$$(8)\quad w_1 = w_1^{\max} - (w_1^{\max} - w_1^{\min}) \cdot \frac{t}{T}$$

where T is the maximum allowed number of iterations. The weighting factors w_2 and w_3 change randomly at each iteration up to maximum values M_2 and M_3:

$$(9)\quad w_2 = M_2 \cdot rand(); \qquad w_3 = M_3 \cdot rand()$$

Values for parameters w_1^{min}, w_1^{max}, M_2 and M_3 are generally problem dependent and will be set on based on parametric analysis.

4. ARTIFICIAL IMMUNE SYSTEMS AND IMMUNE ALGORITHM

IA is a search algorithm based on genetic algorithm principles and on the protection mechanism of living organisms against bacteria, viruses or other microorganisms. Both GA and IA apply similar mechanisms like crossover or mutation. The problem coding is similar in both cases, except that chromosomes in GA are named antibodies in IA. Problem formulation, i.e. objective functions and / or constraints, is coded in antigens. The basic difference between the two algorithms lies in the selection procedure.

GA uses a simple selection mechanism based on fitness function evaluation and a certain selection rule, like the roulette rule. Instead of fitness functions, IA computes affinities between antibodies or between antibodies and antigens. Based on the affinities between antibodies and antigens, and specific control parameters, a selection and reproduction pool, named proliferation pool, is created using antibodies with greatest affinities. The basic IA is described in Box 1.

Affinities computed in step 3 and 7 can be measured using the entropy from the information theory.

Box 1 – The Immune Algorithm.

1. Define antibodies and antigens.
2. Generate initial antibodies population.
3. Compute affinities between antibodies and antigens.
4. Select antibodies with highest affinities and displace them in the proliferation pool.
5. Apply genetic operators (crossover and mutation).
6. Clonal proliferation stage: multiply clones and eliminate from the proliferation pool all clones whose affinities are smaller than a threshold value.
7. Clonal diversification stage: compute affinities between clones and eliminate those clones whose affinities are larger than a threshold value.
8. Generate the new antibodies population based on the clones in the proliferation pool.
9. Stopping criterion or return to step 3.

Thus, for a population of N antibodies, the entropy that measures the diversity of antibodies can be computed as:

$$E_j(N) = -\sum_{i=1}^{N} P_{ij} \cdot \log P_{ij} \quad (10)$$

where P_{ij} is the probability of the i-th allele to be found in the j-the gene. For all the M genes in an antibody, the total diversity is:

$$E(N) = \frac{1}{M}\sum_{i=1}^{M} E_j(N) \quad (11)$$

Thus, the affinity between two antibodies, for example antibodies m and n, can be computed as:

$$AFF_{mn}^{a-a} = (1 + E(2))^{-1} \quad (12)$$

Where $E(2)$ is the diversity computed using only antibodies m and n. On the other hand, the affinity between an antibody m and an antigen g is defined using the objective function of antibody m for the g antigen, OBJ_m^g:

$$AFF_m^g = (1 + OBJ_m^g)^{-1} \quad (13)$$

Both affinities have values between 0 and 1.

5. CASE STUDIES

5.1.Implementation

The dual optimization problem considered in this paper was approached using the two optimization methods briefly described in the previous sections.

The minimum power loss reconfiguration problem was approached using the PSO algorithm. In this stage, the problem of optimal capacitor placement was also considered but at only a preliminary level. A solution of the optimization problem or a particle is described by a coding scheme with two parts:

The first part encodes the radial structure produced by reconfiguring the closed-loop distribution system. A radial reconfiguration solution of the system can be described by a two m-tuples of indices, where the value of parameter m is equal to the sum of the number of source nodes and the number of independent loops in the system, minus one. The first m-tuple indicates the feeders in the system where the loops should be opened; the second m-tuple indicates the line sections on each feeder where the sectionalizing switches must be turned off.The second part encodes the number of capacitors in the nodes of the distribution system.

The reactive power optimal compensation problem was approached using IA. The PSO algorithm was applied to identify a radial solution for the system and an initial solution to the reactive power optimal compensation problem. Then the IA algorithm was run to produce the final solution of the optimization problem. Applying multiple runs of the PSO and IA algorithms a set of suboptimal solutions for the optimization problem can be determined, and the best of then can be chosen as the optimal solution.

This implementation procedure for the PSO and IA was applied for two distribution test systems. The first one was used to tune the parameters of the algorithm, while the second one was a real, more complex distribution system.

5.2. Pilot system

As a pilot system, a distribution network with 2 generator buses, 34 consumer nodes, 8 feeders and 39 line sections was considered. Consumer nodes contain transformers with rated apparent powers equal to 250, 400, 630 and 1000 kVA. Each transformer was loaded to 80% of its rated power. For the power factor, values between 0.80 and 0.85 were considered. The 8 feeders and 39 line sections consist of underground cables with electrical parameters: r_0 = 0.234 Ω/km and x_0 = 0.092 Ω/km. The cable lengths were between 700 m and 3500 m.

The reactive power compensation and capacitor placement problem was applied using 200 capacitor banks with a rated power of 5kVAr each.

The computational procedures described briefly in the previous sections were implemented as Matlab functions and were run to study the results and the convergence proprieties of the algorithms. Few of the results are briefly described below.

For the PSO algorithm, the influence of parameters w_1, w_2 and w_3 was studied. As a general observation, irrespective of their values, the algorithm has high convergence properties. In our experiments, 100 generations were enough to obtain good solutions for the optimal reconfiguration problem. For the first parameter, too narrow intervals (w_1^{min}, w_1^{max}) or too high values of w_1^{max} may produce premature convergence of the algorithm, and too high values of the power losses. Hence the reference values chosen for parameters w_1^{min} and w_1^{max} were 0.5 and 0.9.

The local and global weighting factors w_2 and w_3 may also determine premature convergence. Too different values of parameters M_2 and M_3 discourage the diversification during the search process. At the same time, too high values of the same parameters produce quick convergence to local minima. Hence, for parameters M_2 and M_3 equal values of 1.5 were chosen as reference.

For the IA, the influence of three parameters was studied, namely the values for the mutation rate, the crossover rate, and the length of the crossover window.

The scatter plots from Fig. 1 show that the convergence of the IA is encouraged by high values of the mutation rate. This behavior is normal if one considers the positive effect of diversification produced by these values. However, using too high values for the mutation rate can cause too much randomness in the evolution of the IA. Hence a moderate value of 0.3 was considered in the following analysis.

A similar analysis conducted for the influence of the crossover rate has proven better performances of the IA for higher values of this parameter. The scatter plots in Fig. 2 depict this behavior. Hence, the reference value that was considered further on for the crossover rate was 0.9.

For the length of the crossover window values between 1 and 35 genes were considered. The maximum value of this parameter must not exceed an upper limit imposed by the number of genes from an antibody. As shown in Fig. 3, there is a clear tendency (except a saturation process toward the upper limit) to reduce the convergence rate of the IA when increasing the length of the crossover window. Best results were obtained for a unitary length crossover window. However, too narrow crossover windows may transform the crossover operator into an alternative form of mutation operator. To obtain high convergence properties and to avoid duplicating mutations through crossover operation a value of 4 was used further for the crossover window.

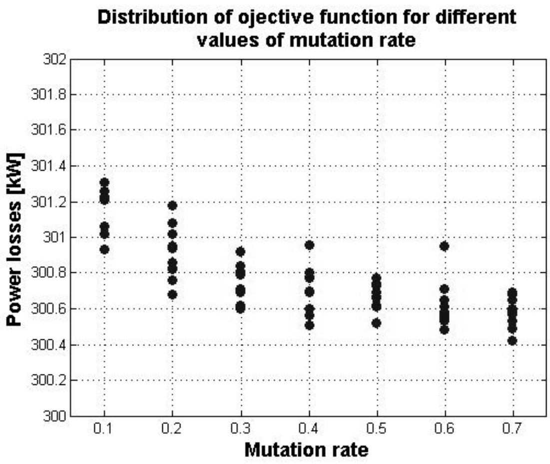

Fig.1. The influence of the mutation rate over the convergence.

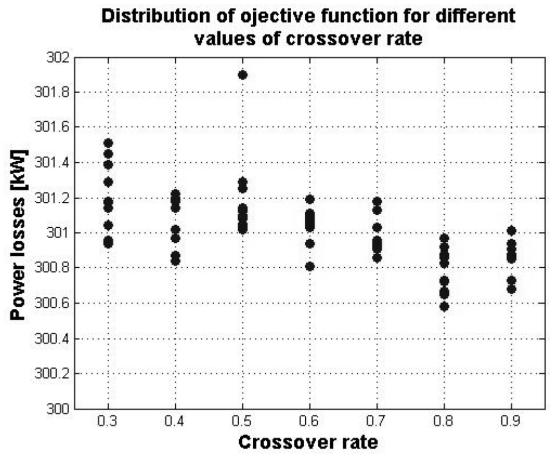

Fig.2. The influence of the crossover rate over the convergence.

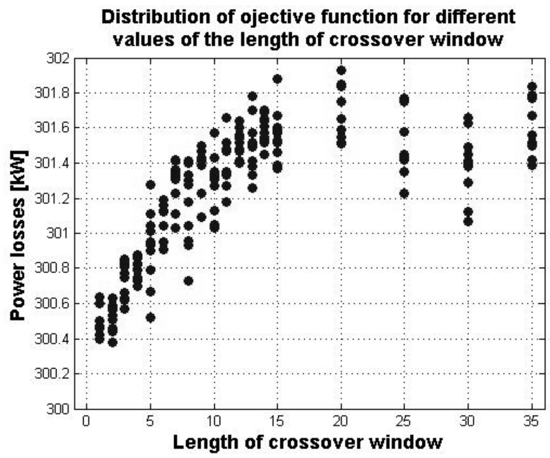

Fig.3. The influence of the crossover window over the convergence.

Table 1 – Solution for the minimum loss reconfiguration problem.

Solution	Line sections													
I	7-8	1-55	37-38	43-59	45-53	35-36	26-27	27-36	14-15	21-22	20-47	19-20	17-18	2-17
II	6-7	48-55	37-38	29-38	44-45	25-54	27-36	12-27	14-15	21-22	7-20	20-47	9-18	17-18
III	60-61	1-48	28-29	41-42	45-53	53-54	26-27	12-27	15-21	21-22	7-20	45-46	9-18	2-17

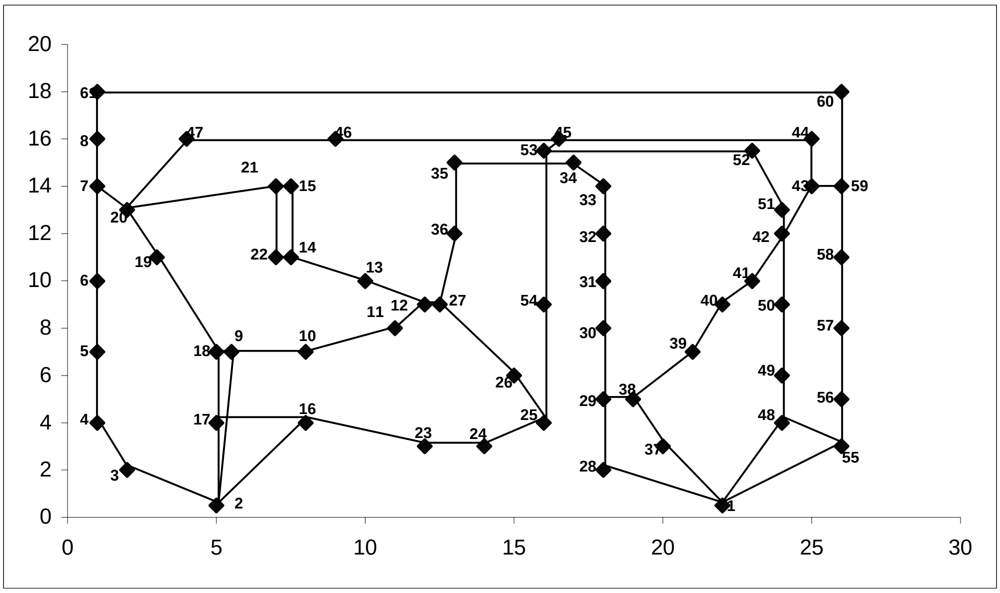

Fig. 4. The structure of the complex test distribution system.

The reference values chosen for the four parameters were used for further studies of the reactive power compensation problem in the pilot distribution system and in the complex test system described bellow. The same problem was solved using a basic implementation of the GA. A comparison between the convergence proprieties of the IA and the GA will be described shortly in the next section.

5.3. Complex test system

The PSA & IA implementation described in the previous sections was further tested using a complex test distribution system with 2 generator buses, 61 consumer nodes, 33 feeders with 73 line sections and a variable stock of capacitors with rated power of 5 kVAr. The transformers in the consumer nodes have rated apparent powers equal to 400 and 630 kVA, and are loaded to degrees of 50-80 %. For the power factor, values between 0.80 and 0.85 were considered. The feeders in the system use underground cables with the same electrical parameters as in the case of the pilot system (see previous section). The structure of the complex test system is presented in Fig. 4.

The values of the parameters used to run the PSO and IA were those chosen based on the analysis conducted for the pilot test system.

During a 100 generations run, the PSO algorithm produces a set of solutions as radial configurations of the distribution system. These configurations, for the last three generations are depicted in Table 1. The last solution is the optimal one found and is shown schematically in the open-loop system from Fig. 5. Using this solution as a reconfigured radial distribution system, the IA algorithm was run to solve the reactive power compensation and capacitor placement optimization problem.

In the initial, uncompensated distribution system, the power losses equal 421.1 kW. After running the IA for 5000 generations, 400 capacitor banks were placed in the system, with a total reactive power of 2000 kVAr, which represents 17.3 % from the system reactive load. This compensation solution determines power losses of 388.2 kW, that is a reduction of 32.9 kW compared with the case of the initial distribution system.

At the level of the algorithm implementation, the results respect the conclusions drawn in the analysis of the pilot distribution system. To compare convergence properties of IA with those of GA, Fig. 6 shows the variation of the objective function's values during the iterative process over 5000 generations for both IA and GA. As this figure shows, the convergence rate of the IA is superior to that of the GA..

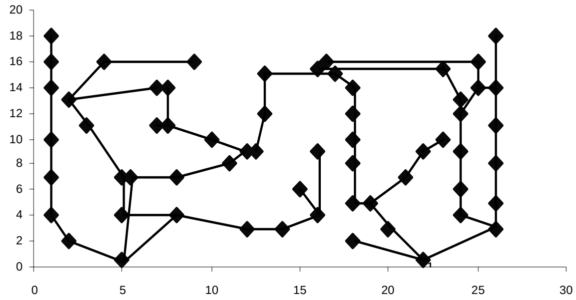

Fig.5. The structure of the complex test distribution system in an open-loop configuration.

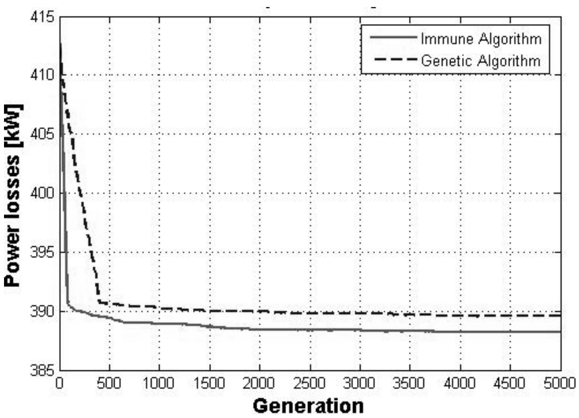

Fig.6. Comparison between the convergence proprieties of the genetic and immune algorithms for the complex test system.

6. CONCLUSIONS

This paper presents a PSO&IA approach to the radial reconfiguration and reactive power compensation problems in distribution systems. The implementation was tested on a pilot distribution system and the values of different parameters of the algorithm were tuned during this analysis. Further on, the Matlab implementation of the PSO&IA was applied to a complex test system to confirm the performances of the algorithm. These tests have proven the feasibility of the proposed method.

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