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Genetic Algorithms for Optimal Reactive Power Compensation of a Power System with Wind Generators based on Artificial Neural Networks

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In this paper, we develop a method to maintain an acceptable voltages profile and minimization of active losses of a power system including wind generators in real time. These tasks are ensured by acting on capacitor and inductance benches implemented in the consuming nodes. To solve this problem, we minimize an objective function associated to active losses under constraints imposed on the voltages and the reactive productions of the various benches. The minimization procedure was realised by the use of genetic algorithms (GA). The major disadvantage of this technique is that it requires a significant computing time thus not making it possible to deal with the problem in real time. After a training phase, a neural model has the capacity to provide a good estimation of the voltages, the reactive productions and the losses for forecast curves of the load and the wind speed, in real time.

Keywords: Optimal Reactive Power, Wind Park, Active Losses, Optimization, Genetic Algorithm (GA), Artificial Neural Networks (ANN).

1. INTRODUCTION

The production companies and energy transport have to ensure the energy supply at various points of consumption with a good quality. These requirements exceed by far, what is allowed in other industrial sectors. Indeed, they must provide energy by taking into account the following items:

- the network stability after a disturbance,
- the voltages stabilization,
- the losses minimization,
- the production cost,
- The breakdowns diagnosis...

One of the most significant problems for the dispatching of power system is to maintain a voltage profile in the standards. In [1-3], the optimal power flow of the power system is ensuring by an optimal placement of reactive compensation devices. To determine the optimal reactive productions of these devices, we must minimize the active losses of the power system. For this type of optimization problem, the traditional methods (simplex, linear penalty...) require a preliminary expertise on the problem, complex mathematical tools and sometimes difficult to implement. Moreover, convergence is not always assured. However, GA are simple to establish and do not require a preliminary knowledge of the problem [4-7].

In this paper, we present a suitable method for maintaining an acceptable voltages profile and minimization of active losses of an electrical power system including a wind park by acting on benches of capacitors and inductances established in the consuming nodes. This method initially consists in making turn the program of the load flow to determine the

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initial conditions of the problem to be optimized. In this stage, we supposed that the wind node is a consumer [8, 9]. Then, we minimized the active losses under constraints imposed on the voltages and the reactive productions of the various benches by the use of genetic algorithms for a total active power demanded and a wind speed. The solution of the problem takes a significant computing time. Its real-time operation is then impossible.

In a second stage to overcome this drawback, we present a method able to provide solutions in real time based on the training techniques of an artificial neural network applied to the electrical supply network [10]. Indeed, having a data base collected by the solutions of the optimization program based on genetic algorithm, the neural network was involved to be able to provide solutions for a given situation in real time and to predetermine solutions for forecast curves of the load and the wind speed.

Simulations were made on the Tunisian power system comprising 20 nodes, 26 lines, 6 machines and a wind farm based on induction machines. The simulation results show the effectiveness of the adopted procedure.

2. PROBLEM FORMULATION

In order to describe the problem by a mathematical model, we adopt the following assumptions:

- The voltages of the producing nodes, only of the wind node, are constant. Indeed, the connected generators to these nodes are synchronous types and thus equipped with voltage regulators.
- The currents of the loads are constant for a given power.

2.1. Power system modelling

By application of the method of uncoupled Jacobian [8], we obtain the following relation:

$$\underline{\Delta V} = J_{qv}^{-1} \ \underline{\Delta Q} \tag{1}$$

with: $\underline{\Delta Q}$ is the increment vector of reactive powers, dimension ($n_c \times 1$); $\underline{\Delta V}$ is the increment vector of consuming nodes voltages, dimension ($n_c \times 1$); J_{qv} is the Jacobian matrix describing the sensitivity of the reactive powers compared to the voltages, dimension ($n_c \times n_c$) and n_c is the number of consuming nodes.

The assessment node *n* assumes the losses. Thus, the injected active power in this node is expressed as follows [8]:

$$P_n = P_{gn} - P_{dn} = \sum_{j=1}^{n-1} Y_{nj} V_n V_j \cos(\alpha_{nj} - \theta_{nj}) \tag{2}$$

Or:

$$P_n = P_D + p - P_{dn} - \sum_{i=1}^{n-1} P_{gi} \tag{3}$$

where P_D is the total requested power ; P_{dn} is the partial consumption of node *n ;* Y_{nj} and θ_{nj} are the size and the argument of the element *(n, j)* of the nodal admittance matrix ; V_i and α_i are the size and the argument of the tension $\overline{V}_i$ in node *i* and $\alpha_{nj} = \alpha_n - \alpha_j$.

Any variation on the voltage vector $\underline{\Delta V}$ involves a variation of the active losses according to the following expression:

$$\Delta p = \sum_{j=1}^{n_c} V_n Y_{nj} \cos(\alpha_{nj} - \theta_{nj}) \, \Delta V_j \tag{4}$$

Equations (1) and (4) give:

$$\Delta p = \sum_{k=1}^{n_c} (\sum_{j=1}^{n_c} V_n Y_{nj} \cos(\alpha_{nj} - \theta_{nj}) \, J_{qv\ jk}^{-1}) \Delta Q_k \tag{5}$$

this can be written as the following condensed form:

$$\Delta p = \underline{R}_c^T \underline{\Delta Q} \tag{6}$$

where the elements of the vector $\underline{R}_c$ are defined as follows:

$$R_{c_k} = \sum_{j=1}^{n_c} V_n Y_{nj} \cos(\alpha_{nj} - \theta_{nj}) \, J_{qv\ jk}^{-1} \tag{7}$$

Equation (6) can be rewritten as:

$$p = p_o + \underline{R}_c^T \underline{\Delta Q} \tag{8}$$

where p is the total active loss of the power system, and p_o is the initial active losses.

The problem to be solved consists in minimizing the active losses defined by equation (8) under the following constraints:

$$\begin{cases} V_{\min} \le V_o + J_{qv}^{-1} \ \underline{\Delta Q} \le V_{\max} \\ \Delta Q_{\min} \le \Delta Q \le \Delta Q_{\max} \\ p_o + \underline{R}_c^T \underline{\Delta Q} \ge 0.1 \end{cases} \tag{9}$$

with: $V_{\min}$ and $V_{\max}$ are the minimum and the maximum voltages; $\Delta Q_{\min}$ and $\Delta Q_{\max}$ are the minimum and the maximum reactive powers produced by capacitors and inductances established in consuming nodes and $\underline{V}_o$ is the initial vector voltage.

To resolve the optimization problem defined by equations (8) and (9), it is necessary to carry out the program of load-flow applied to the studied network. Thus, from the last iteration of the program, we determine the opposite Jacobian matrix J_{qv}^{-1}, the active losses p_o and the vector of voltages of the consuming nodes $\underline{V}_o$. Then, we can deduce the sensitivity vector $\underline{R}_c$. The resolution of the problem uses genetic algorithms.

2.2 Wind generator modeling

The mechanical power obtained from the wind turbine is given by the following equation [11]:

$$P_m = \frac{1}{2} \rho \pi R^2 V_w^3 C_p \tag{10}$$

where ρ is the air density (1.22 kg.m^{-3}), R (m) is the length of the blade, V_w (m.s^{-1}) is the wind speed and C_p is the power coefficient. The tip speed ratio is defined as the ratio of the wind turbine Ω to the wind speed [11]:

$$\lambda = \frac{\Omega \ R}{V_w} \tag{11}$$

The power coefficient represents the aerodynamic efficiency of the turbine and depends on the tip speed ratio λ and the pitch angle β. For the used wind turbine, the following form is used to approximate this coefficient as a function of λ and the pitch angle β [12]:

$$C_p(\lambda,\beta) = (0.44 - 0.0167\beta)\, s\,\text{in}\left(\frac{\pi \ \ (\lambda - 3)}{15 - 0.3\beta}\right) - 0.0184\ (\lambda - 3)\ \beta \tag{12}$$

3. OPTIMIZATION BY GENETIC ALGORITHMS

In this work, we have used real-code implementation. In fact, the use of real parameters makes it possible to use large domains, even unknown domains, for the variables, which is difficult to achieve in binary implementations where increasing the domain would mean sacrificing precision, assuming a fixed length for the individuals. Another advantage when using real parameters is their capacity to exploit the gradualism of the functions with continuous variables, where the concept of gradualism refers to the fact that slight changes in the variables correspond to slight changes in the function [13,14].

Although there are many possible variants of the basic GA, the fundamental underlying mechanism operates on a population individuals, which representing possible solutions to the problem, and consists of three operations:

1. Evaluation of individual fitness,
2. Formation of a gene pool (intermediate population) through selection mechanism and
3. Recombination through crossover and mutation operators.

Genetics algorithms (GA) implemented in the presented work is reported in the following algorithm [3]:

i) Select randomly a population of generated individuals ΔQ_i as:

   $\Delta Q_i = \Delta Q_{\min} + \beta\,(\Delta Q_{\max} - \Delta Q_{\min})$, where β is a random real number belonging to the interval [0 1].

ii) Evaluate the fitness of each individual and determine the best one which is always transferred to the next generation by calculating the active losses according to this equation:

   $$p = p_o + \underline{R}_c^T \underline{\Delta Q}$$

   Select individuals for reproduction with the tournament selection strategy.

iii) Apply the crossover operator with a probability equal to 0.9 to favour exchange of genetic information among the population. Each two parents $\Delta Q_1 = \left[\Delta Q_{11} \cdots \Delta Q_{1n_c}\right]$

and $\Delta Q_2 = \left[\Delta Q_{21} \cdots \Delta Q_{2n_c}\right]$ give two children $\Delta Q_1^{'} = \left[\Delta Q_{11}^{'} \cdots \Delta Q_{1n_c}^{'}\right]$ and $\Delta Q_2^{'} = \left[\Delta Q_{21}^{'} \cdots \Delta Q_{2n_c}^{'}\right]$, where $\Delta Q_{ij}^{'}$ is a value of the interval $\left[C_{\min} - \chi I, C_{\max} + \chi I\right]$, with: $C_{\min} = \min(\Delta Q_{1i}, \Delta Q_{2i})$, $C_{\max} = \max(\Delta Q_{1i}, \Delta Q_{2i})$, $I = C_{\max} - C_{\min}$ and $\chi = 0.5$

iv) Use the mutation operator with probability equal to 0.01 by replacing the old individual $\Delta Q = \left[\Delta Q_1 \cdots \Delta Q_{n_c}\right]$ by the new one $\Delta Q^{'} = \left[\Delta Q_1^{'} \cdots \Delta Q_{n_c}^{'}\right]$, as:

$$\Delta Q_i^{'} = \begin{cases} \Delta Q_i + \Delta(t, \Delta Q_{i\max} - \Delta Q_i) & if \quad \tau = 0 \\ \Delta Q_i - \Delta(t, \Delta Q_{i\max} - \Delta Q_i) & if \quad \tau = 1 \end{cases}$$

$$\Delta(t, y) = y \cdot \left(1 - r^{(1 - \frac{t}{g_{\max}})^{\delta}}\right)$$

τ is a random integer (0 or 1), r is a random real ($\in [0,1]$), $g_{\max}$ is the maximum number of generations and $\delta = 5$.

v) Check for convergence by measuring the diversity of the population. If the population diversity has fallen under a preselected threshold (10^{-5}), go to step (i); otherwise, go to step (ii).

It must be stressed that this algorithm does not reflect a genetic algorithm in its most general form, the size of the population being able to be not constant and the crossing, which can imply more than two individuals. Moreover, great number of operator of selection, crossing and change were proposed for various representations or applications, which are not presented here.

4. SIMULATION RESULTS

4.1. Presentation of the studied power system

The simulated power system is composed into 20 nodes, 7 generators and 26 lines. The generator G_W is the studied wind power station as shown in figure 1. It is considered that the wind park consists of three identical machines and that these machines receive the same wind.

We defined a participation factor F_c in order to characterize the distribution of the requested total power P_D at various nodes. Another distribution factor noted F_g, which characterizes the distribution of the total generated power at the various producing nodes. Each node is connected to a load for which its power-factor $\cos \phi_c$ is assumed to be constant. So, we have:

$$\begin{aligned} \underline{P}_g &= \underline{F}_g \; P_D \\ \underline{P}_c &= \underline{F}_c \; P_D \\ Q_{ci} &= P_{ci} \; tg(\phi_{ci}) \end{aligned} \qquad (13)$$

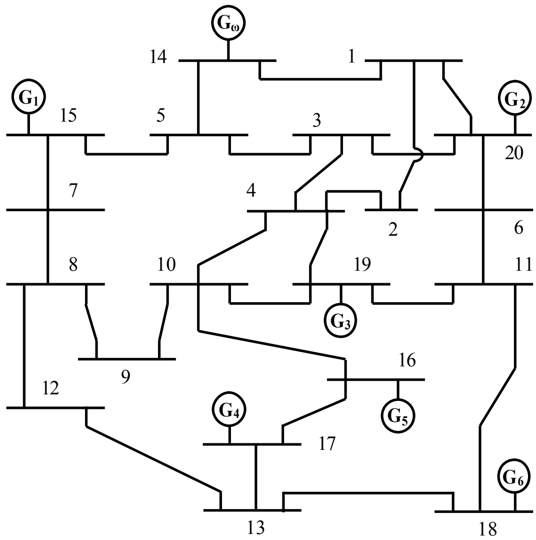

Figure 1: Structure of the studied power system

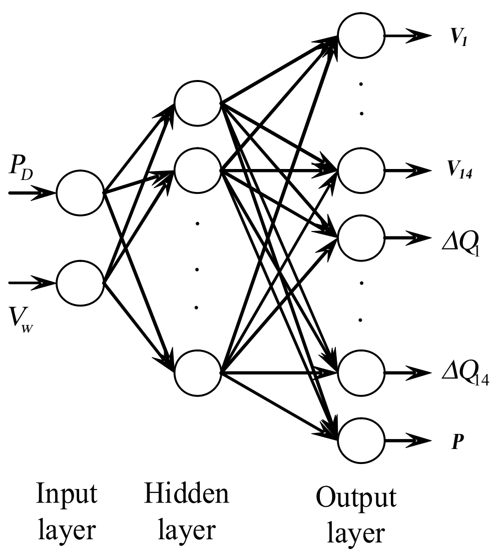

Figure 2: Structure of the ANN

TABLE I: Constraints of the optimization problem

V_{min} (pu)	V_{max} (pu)	ΔQ_{min} (pu)	ΔQ_{max} (pu)	p (pu)
0.95	1.05	-0.15	0.15	0.001

4.2. Simulation results of the genetic algorithms (GA)

The constraints of the optimization problem, described by equations (9), are summarized in table I. As an illustration we consider the case where the power requested $P_D = 3.5\ pu$ and the wind speed $V_w = 14\ m/s$. Figures 3, 4 and 5 show the evolution during iterations of the losses, of the productions of the reactive elements connected at the consuming nodes and of the voltages of the same nodes.

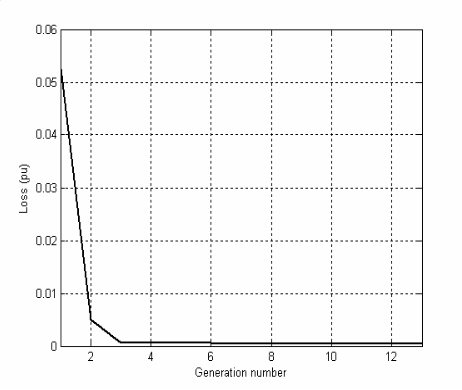

Figure 3: Evolution of the losses during iterations

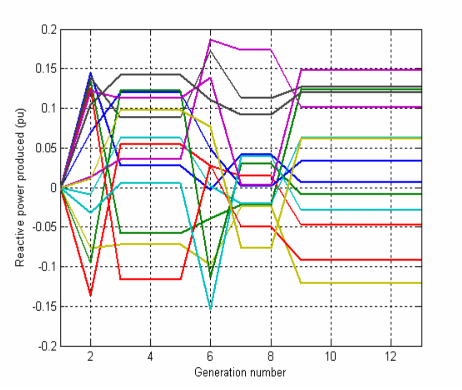

Figure 4: Evolution of the reactive productions during iterations

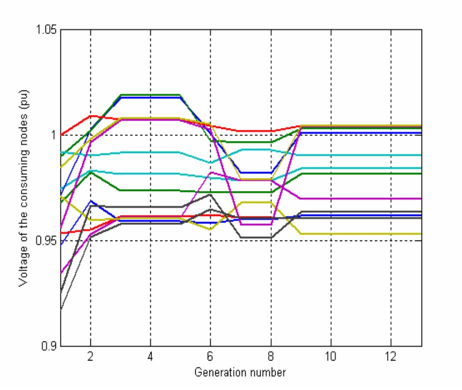

Figure 5: Evolution of the voltages of the consuming nodes during iterations

In this simulation, all the initial reactive productions are null, whereas all the voltages of the consuming nodes leave the solution of the load flow problem. Figures 3, 4 and 5 show the convergence of the genetic algorithms. Indeed, during iterations the losses decrease and the reactive productions as well as the voltages of the consuming nodes obey the imposed constraints.

4.3. Application of the neural networks

Artificial neural networks (ANN) are mathematical models, which are made up of non-linear computing units. These units are connected through weights whose values are adaptive parameters which are updated to map a mathematical function. ANNs have shown a great aptitude to confront various types of complex modelling problems. They have the capacity to learn by adapting their parameters. Weights are calculated by iterative training algorithm described by mathematical rules. The most often used architecture is the so-called multi-layer. The back-propagation algorithm is the most used algorithm for the training of the multi-layer networks [10]. The structure of the used ANN has two input units, one hidden layer and one output layer, this structure is depicted in figure 2.

Comparison of the ANN results with the GA

A comparison of the obtained results by the ANN and with the GA is performed for various operating points, which are defined by the wind speed V_w and the required active power P_D. These results are shown in the table II where computations are done in a *Pentium 4, 3.06 GHz*. The index ***ga*** and ***nn*** indicate the obtained results from GA and from ANN, respectively. Table II proves that results yielded from ANN coincide accurately with those given by GA. The execution time with ANN is much smaller than with GA, so we can use ANN in real time.

Application of the neural network

The data base is made by 1500 random values computed by the GA, which correspond to a wind speed ranging between 12 and 18 (m/s), and a consumed power ranging between 0.5 and 4 (pu) to guarantee a good training algorithm.

We used the forecast curves of the requested total active power and the wind speed during a period of 24 hours. These curves are represented on figures 6 and 7.

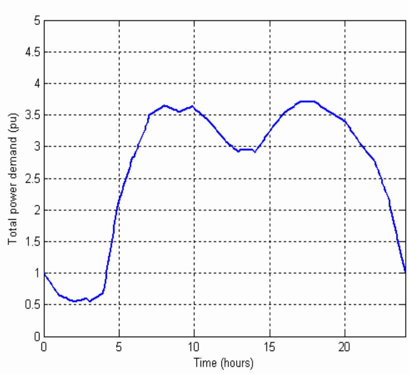

Figure 6: Forecast total consumed power

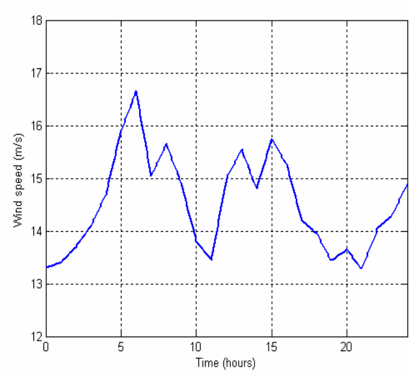

Figure 7: Forecast wind speed

After training of the ANN, the obtained simulation results with the presented micro grid are shown on figures 8-14.

The active losses given on figure 8 are practically negligible that shows the effectiveness of the optimization algorithms. As illustration, we present the simulation results relative to the nodes 1, 2 and 3.

TABLE II: Comparison between results yielded from ANN and the ones yielded from GA

		$V_w = 13.5\,ms^{-1}$ $P_D = 2.5\,(pu)$	$V_w = 14\,ms^{-1}$ $P_D = 3.5\,(pu)$	$V_w = 15\,ms^{-1}$ $P_D = 3\,(pu)$	$V_w = 16\,ms^{-1}$ $P_D = 2\,(pu)$
Bus voltages (pu)	V_{1ga}	0.9670	0.9654	0.9656	0.9634
	V_{1nn}	0.9634	0.9588	0.9605	0.9648
	V_{2ga}	0.9796	0.9765	0.9821	0.9798
	V_{2nn}	0.9788	0.9756	0.9765	0.9818
	V_{3ga}	0.9612	0.9582	0.9599	0.9682
	V_{3nn}	0.9635	0.9611	0.9629	0.9674
	V_{4ga}	0.9850	0.9829	0.9847	0.9839
	V_{4nn}	0.9839	0.9807	0.9819	0.9873
	V_{5ga}	0.9666	0.9675	0.9636	0.9593
	V_{5nn}	0.9629	0.9713	0.9694	0.9691
	V_{6ga}	0.9807	0.9578	0.9857	0.9779
	V_{6nn}	0.9744	0.9746	0.9756	0.9776
	V_{7ga}	0.9510	0.9572	0.9716	0.9542
	V_{7nn}	0.9720	0.9640	0.9607	0.9671
	V_{8ga}	0.9913	1.0028	1.0272	0.9842
	V_{8nn}	1.0090	1.0002	0.9970	1.0063
	V_{9ga}	1.0040	1.0138	1.0261	0.9952
	V_{9nn}	1.0150	1.0056	1.0039	1.0118
	V_{10ga}	1.0112	1.0130	1.0115	1.0008
	V_{10nn}	1.0109	1.0057	1.0061	1.0099
	V_{11ga}	0.9980	0.9929	0.9942	0.9946
	V_{11nn}	0.9924	0.9933	0.9931	0.9942
	V_{12ga}	0.9833	0.9899	1.0302	1.0195
	V_{12nn}	1.0019	0.9825	0.9801	1.0052
	V_{13ga}	0.9909	1.0008	1.0162	0.9977
	V_{13nn}	0.9987	0.9966	0.9919	1.0022
	V_{14ga}	0.9502	0.9703	0.9696	0.9652
	V_{14nn}	0.9641	0.9589	0.9638	0.9685
Computing time (s)	t_{ga}	35.8130	42.9370	32.4850	32.1410
	t_{nn}	0.0460	0.0320	0.0310	0.0470

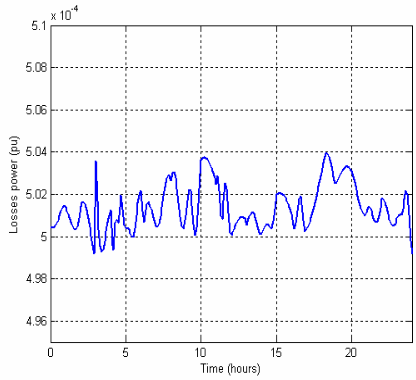

Fig. 8. Total loss power

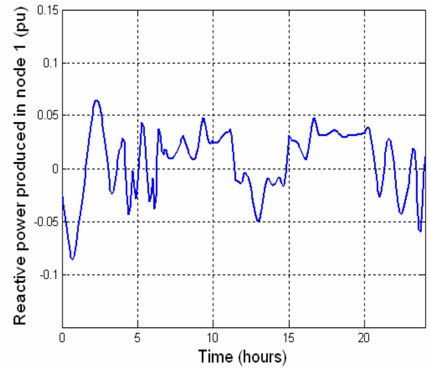

Figure 9: Reactive power produced in node 1

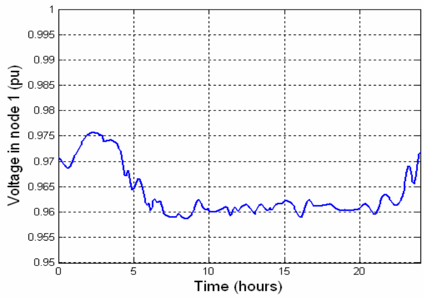

Figure 10: Voltage of the node 1

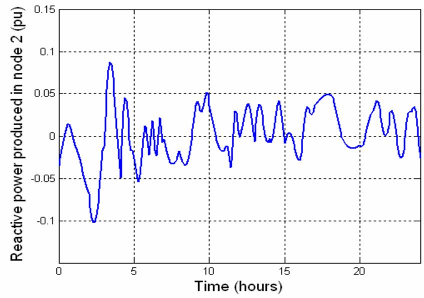

Figure 11: Reactive power produced in node 2

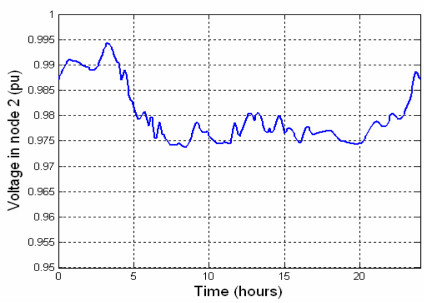

Figure 12: Voltage of the node 2

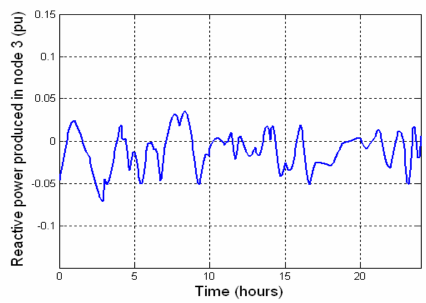

Figure 13: Reactive power produced in node 3

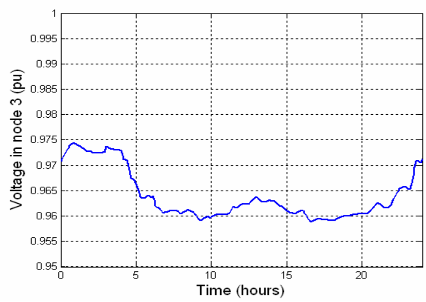

Figure 14: Voltage of the node 3

Simulation results, presented in figures 9-14, show that all the reactive productions and the voltages of the consuming nodes evolve in their allowed bands. Figure 9, 11 and 13 show the reactive powers produced in nodes 1, 2 and 3, respectively. If the reactive productions are positive, they are produced by capacitors benches. If the reactive productions are negative, we must connect inductances benches to improve the voltages. In the same way, figures 10, 12 and 14 show the voltages of nodes 1, 2 and 3, respectively. These figures prove that the voltages are sensitive to the total consumed power.

5. CONCLUSION

This paper presents the use of genetic algorithms for the resolution of the optimization problem of the voltages plan and the active losses in a power system including a wind power station by acting on the reactive productions of inductances and capacitors benches connected to the consuming nodes. To approach the case of a real network, we have simulated the forecast curves of the wind speed and the total power demand. The previous procedure takes a large computing time and consequently the analysis of the results in real time becomes impossible. To overcome this difficulty, we used an artificial neural network. The comparison of obtained results with the previous method and with the ANN proves the effectiveness of the neural model. The study of the considered power system shows that the optimization algorithm converges towards acceptable results with a significant computing time.

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