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Neural Control of Voltage for a Synchronous Generator

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Abstract

This article presents the regulation of the voltage of a synchronous generator using a neural network called "Neocognitron". A system of test machine bus-infinite is used, where the synchronous generator is connected to an infinite bus through external impedance. The methodology is described used for the neural control, the obtained results of this control type are presented and they are compared with results obtained with a conventional control of the type ST1. It is shown that the neural control has a better answer in the time and bigger robustness before big perturbations.

Keywords – Cell, Conventional Control ST1, Neocognitron, Neural Control, Synchronous Generator.

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1. INTRODUCTION

The connection of the synchronous machines in parallel, demands that the generators have agreement of phases, the same frequency and the same voltage in terminals. To be able to fulfil with these mentioned requirements, equipment is needed that controls the speed, power and the voltage in terminals of the generators. During the last twenty years, a great effort has been made to get new developments and technical of non conventional control that can increase or to replace the conventional control techniques. A number of technical of non conventional control has evolved, offering solutions to many problems of the control in the industry. This is the essence of what the practical control has been called [1], that is a collection of techniques that the engineers practicing has found efficiently and easily to use in the field The intelligent controls are characterized by their ability of establishing a functional relationship between their inputs and outputs with empiric data, without the resource of explicit models of the controlled systems. On the contrary of the conventional controls, the intelligent controls can learn to remember and to make decisions.The intelligent controls can train to operate indeed under conditions of uncertainty, they can respond autonomously to unexpected situations, without the intervention of the operator of the system.The artificial neural networks are very appropriate tools for the modelling and control. They have the capacity to learn for the adjustment of internal parameters through the experience, they have good properties of robustness with regard to incomplete information and with noise, offering an attractive approach for the calculation of processes in the field and for the modelling of plants [2]. The properties that make to the artificial neural networks particularly applicable to control applications they are the following ones:

To be nonlinear by nature, they are specially prepared for the control of nonlinear plants, they are directly applicable to the control multivariable and they are relatively tolerant to flaws due to their parallel structure, besides that they face new situations and they have the ability to generalize The neural network denominated "Neocognitron" was developed by Kunihiko Fukushima with Sei Miyake's assistance and Takayuki I. around the years 70 and 80. The neocognitron is a design of network multi-layers that consists of connections on form of cascade of many layers of cells. It is a network with hierarchy with layers that correspond to simple and complex cells, with a very spread and located connection model among the layers The neocognitron none alone it is the typical neuronal network with hierarchy, it is also the longest and the most complicated neural network developed [3]. The basic function of the neocognitron is to act like a network of recognition of models for images. The main advantage of the neocognitron is the ability to correctly not ecognize single learning models if not also models with partial movement, rotation and another type of distortion.

2. THE NEOCOGNITRON

The neocognitron is a neural network with parallel hierarchy designed for the recognition of hand written characters [3-5]. These network this inspired one in the biological visual pattern of Hubel and Wiesel. They acquire the ability to recognize robust visual models through the learning.The neocognitron carries out an extraction process of characteristic by means of successive filtrates of the entrance image with layers connected in cascade. Each layer extracts the appropriate characteristics from the exit of another previous one and it forms a compressed representation of those extracted characteristics. The classification is achieved by a firm extraction.

2.1 The structure of the neocognitron

The structure of the neocognitron is shown in the Fig. 1 and emerges of a hierarchy of extracting features. An appropriate stage of the neocognitron is believed for each hierarchy stage to extract features. The network however contains an additional stage, labeled as stage 0 that is not used, in contrast with the stages but high, for the extraction of features. The total number of stages of the neocognitron depends on the complexity of the problem.

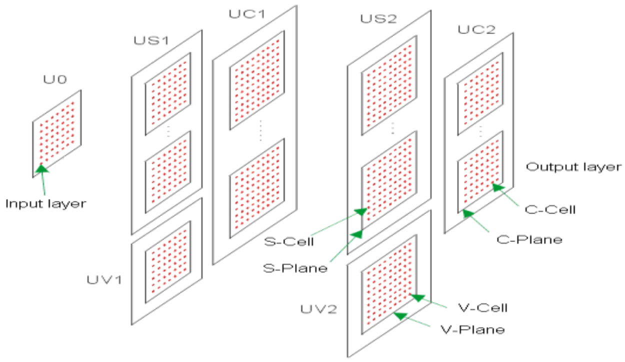


Fig. 1 The structure of the neocognitron.

In the stage 0 of the neocognitron alone the presented pattern is retained, also the alone stage 0 contains the input layer and it is proposed to retain the pattern presented to the network. In the highest stages in the neocognitron the extraction of features is developed. The highest stages consist of two types of layers: the S-layer composed by S-cells proposed for the extraction of features. The C-layer composed by C-cells, proposed to assure a tolerance of changes of the features extracted in the S-layer previous. The cells denote the basic element of operation. The cell is an element or neuron that it processes input values according to a certain rule and it produces output values. There are three types of elementary cells that differ for their function: The receptor cell is the simplest type of cell. Their function is alone to retain the presented models, the S-cell is the most important type in the neocognitron and they has the function of extracting features of the input layer and the C-cells whose function is to assure a tolerance of change in the features extracted by the S-cells.

2.2 Mathematical description of a S-cell.

The function of a S-cell is to extract a feature of a certain position in the input layer. And their mathematical description is shown in the equation (1).

$$u_{sl}(n,k) = r_l \cdot \phi \left[\frac{1 + \sum_{k=1}^{K_{cl-1}} \sum_{v \in A_l} a_l(v,k,K) \cdot u_{cl-1}(n+v,K)}{1 + \frac{r_l}{1+r_l} \cdot b_l(k) \cdot u_{vl}(n)} - 1 \right] \quad (1)$$

Where:

l Serial number of the stage.
n Position of the cell.
k Serial number of the cell plane.
r_l Parameter of selectivity.

K_{cl-1} Number of cell planes in the C-layer previous.
v Position in the connection area.
A_l Area of connection of the S-cell.
a_l, b_l Weighted connections a y b≥0.

$$\varphi[x] = \begin{cases} x & si \quad x \geq 0 \\ 0 & si \quad x < 0 \end{cases}$$

2.3 Mathematical description of a C-cell.

The mathematical description of a C-cell is shown in the equation (2); each C-cell evaluates outputs of the S-cells of a certain connection area.

$$u_{cl}(n,k) = \psi\left[\sum_{k=1}^{K_{cl-1}} j_l(K,k) \cdot \sum_{v \in D_l} d_l(v) \cdot u_{sl}(n+v,K)\right] \qquad (2)$$

Where:
l Serial number of the stage.
n Position of the cell.
k Serial number of the cell plane.
K_{sl-1} Number of cell planes in the S-layer previous.
j_l Connection factor.
v Position in the connection area.
D_l Area of connection of the C-cell.
d_l Weighted connections d ≥0.

$$\psi[x] = \frac{\varphi[x]}{1+\varphi[x]}, \qquad \varphi[x] = \begin{cases} x & si \quad x \geq 0 \\ 0 & si \quad x < 0 \end{cases}$$

2.4. Learning of the neocognitron.

The learning is the process during which the net neuronal adapts to solve a desire task. The learning of the network is controlled by a teacher or without supervision. This task is to determine that features will be extracted in the stages of the network and to prepare the models of training before beginning the learning.
The learning of the neocognitron benefits stage for stage from the lowest stage in the network adjusting the amendable weighted connections weighted a, weighted b according to the learned answer of the network to represent a model of training.

The mathematical description of the learning is shown in the equation (3).

$$\begin{gathered} \Delta a_l(v,K,\hat{k}) = q_l \cdot c_l(v) \cdot u_{cl-1}(\hat{n}+v,K) \\ \Delta b_l(\hat{k}) = q_l \cdot u_{vl}(\hat{n}) \end{gathered} \qquad (3)$$

Where:
l Serial number of the stage.
a_l, b_l y c_l Weighted connections a, b y c≥0.
q_l Learning coefficient.
$\hat{k}$ Serial number of the cell plane.
$\hat{n}$ Position of the activation cell.

3. THE NEOCOGNITRON TO REGULATE THE VOLTAGE OF THE SYNCHRONOUS GENERATOR

It is known that the function of an automatic regulator of voltage it is to adjust the level of excitement of a synchronous machine continually before different conditions of operation of the machine with the purpose of maintaining the voltage in terminals with the smallest quantity in possible variations, guaranteeing the stability of the system under normal conditions of operation. Leaving of this objective, you proceed to apply the neural methodology to regulate the voltage of the synchronous generator.

The proposed control strategy should make that the neocognitron learns the behavior of an automatic regulator of voltage and to be able to improve this behavior it is necessary that the learning of the network is for different points of operation of the system. The inputs of the neocognitron should be chosen with much care in such a way that they generate the necessary minimum quantity of conditions to represent the dynamics of the system.
It is important to mention that several structures of the neocognitron exist and it stops effects of the simulation the structure it was used shown in the figure 3. The structure of the proposed neocognitron consis ts of a input layer of cells, two layers of S-cells and two layers of C-cells; one of these C-layers represents the layer of output cells.The input layer as it is shown in the Fig. 2 this compound one for two input cells, one represents the error defined by the difference between the reference voltage and the voltage in terminals of the generator and the other one to the variation of the error defined by the difference between the current error and the state previous of this error. The two layers of S-cells that are composed by 12 S-cells each one, and the two layers of C-cells that a this compound one for 12 C-cells and the other layer of C-cells that represents to the output layer composed by a C-cell that like leave in the Fig. 2 it contains the output variable represented by the field voltage, since this variable allows us to generate the appropriate control law for our control system.

In the beginning of the learning with teacher one has a group of weighted a, weighted b in the network. Finally the teacher adjusts the weighted of the cells according to the equations mentioned in the mathematical description of learning. In principle, an input pattern is presented in the input layer and the fact spreads through the network. Then it is allowed to increase the weighted to make adjustments according to the specific algorithm of optimization.The input data for the training are an important part of the process of training because the group of data is the only information that the neural network has to learn the task. The fact of training should embrace the operation range for the neural network so that it estimates the wanted output.

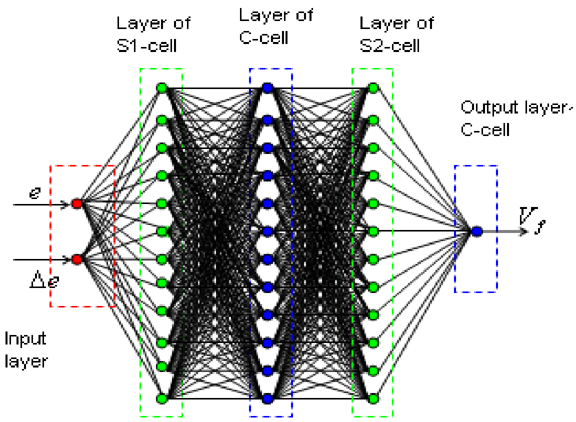


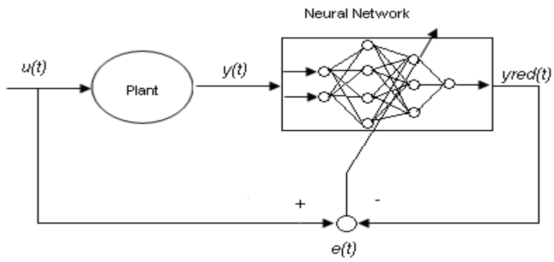
Fig. 2 The structure of the neocognitron used for voltage regulation.

To obtain the data of training the synchronous machine it is simulated with a conventional control ST1, generating input-output data for different operation conditions.To carry out the learning process we take the algorithm of training of the neocognitron, providing as vectors or input patterns to the network the error and the variation of the error, the error is given by the difference of the reference voltage and the real voltage obtained in the terminals of the machine, the variation of the error is determined by the difference between the current error and the previous error, therefore the input and output of the neural network for the learning process are shown in the equation (4).

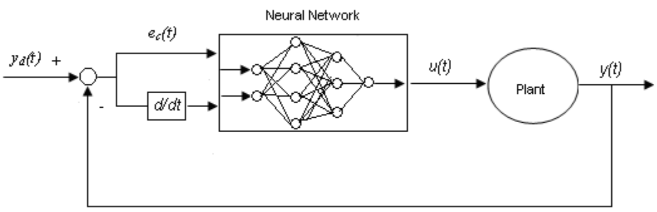
$$e(t) = V_{ref} - V_T(t)$$
$$\Delta e(t) = e(t) - e(t-1) \qquad (4)$$
$$\Delta u(t) = u(t) - u(t-1)$$

With these input vectors it is carried out we was carried out the learning process until reaching a quadratic sum of the maximum error of 0.001 that allows to evaluate that the network has learned the behavior of the system. The wanted output vector is more the variation of voltage of necessary field to maintain the voltage in terminals him near the reference value similar to 1.0 for unit for our study.

The Fig. 3 shown the outline of the inverse control used for this simulation in two stages.



Stage a



Stage b

Fig. 3 Neurocontrol for the dynamic system; Stage a: Identification, Stage b: Control.

The inverse control offers a solution to the problem of control. The inverse control consists of two stages: the first stage a; it is the identification stage where a neural network trains to behave that is to say as the inverse of the system that will be controlled and the second stage b; is the control stage where the same network is used to make the control of the system.

4. RESULTS OF THE SIMULATION

For effects of the simulation the development of the control is based on a connected synchronous generator to an infinite bus through a line of equivalent transmission, a mathematical model of 5º order is used for the representation of the synchronous machine. Appendix A.The tests were carried out with the same parameters of the synchronous machine and under the same operation conditions, allowing to make the comparison of the system of neural regulation with the system of regulation of the type ST1 and this way to evaluate the index of acting of each regulator. For the tests it is shown: the voltage in terminals Fig. 4, the angle of load of the rotor Fig. 5, the active power Fig. 6, the voltage of field Fig. 7, and the index of acting of the voltage in terminals Fig. 8.For the application of the regulation systems we take several groups of conditions initials, they were proven for damping of different times of duration. The time in that it happens the short circuit is of 1 second taking the bus voltage to 0 for unit, for a damping with 12 duration cycles, the final time of the simulation is of 8 seconds. The point of initial operation of the voltage in terminals that it is used for this test is $V_t = 1\angle 7°$ for unit and with an active power of P = 0.8240 for unit.

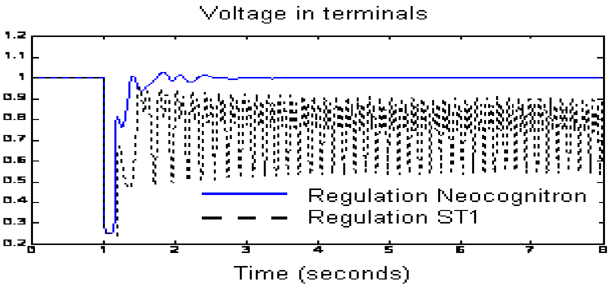


Fig. 4 Voltage in terminals.

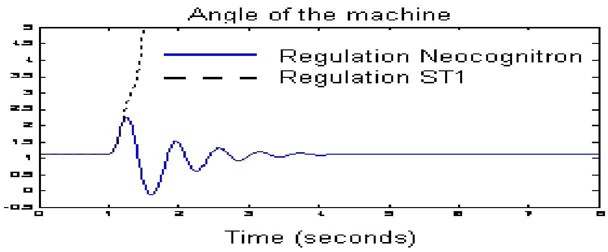


Fig. 5 Angle of load of the rotor.

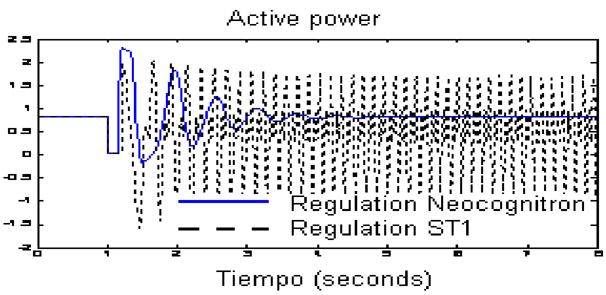


Fig. 6 Active Power.

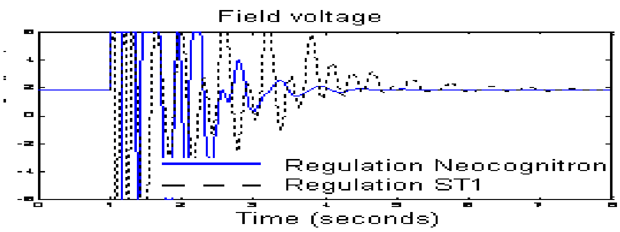


Fig. 7 Field Voltage.

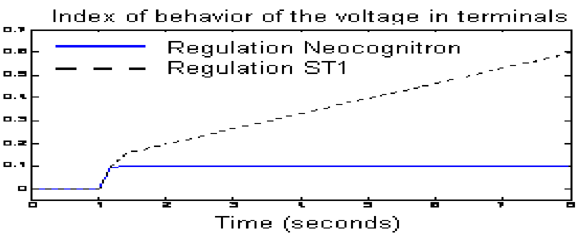


Fig. 8 Index of the quadratic error of the voltage in terminals.

5. CONCLUSION

The motivation of this work is to take advantage of the modern technology of the intelligent control to obtain a better potential in the stability of the system of power low short circuits.The proposed regulator enjoys the general advantages of the neural networks like generalization capacity, tolerance to damping and the property of adaptability due to its learning The results of the simulation of the regulator proposed on several operation conditions and disturbances, demonstrated that the system of voltage regulation based on the neocognitron obtains a better answer in the time that the conventional regulator ST1, as well as a bigger robustnessWe can conclude that the voltage in terminals when the control neuronal is used it is more constant an d with smaller oscillations that when the conventional control is used.

APPENDIX A

The differential equations of the pattern of 5º order, used in this work are [6].

$$p\delta_r = \omega_0 s$$
$$Mps = -K_d s + Tm - Te$$
$$T'_{d0} pe'_q = V_f - (X_d - X'_d)i_d - e'_q$$
$$T''_{d0} pe''_q = e'_q - (X'_d - X''_d)i_d - e''_q$$
$$T''_{q0} pe''_d = (X_q - X''_q)i_q - e''_d$$
$$e''_d = V_d + r_a i_d - X''_q i_q$$
$$e''_q = V_q + r_a i_q + X''_d i_d$$
$$Te = e''_d i_d + e''_q i_q - (X''_d - X''_q)i_d i_q$$

Without loss of generality, the transmission line is described by an equivalent impedance of Thevenin. Therefore, the terminal voltage and their components in direct axis and axis in quadrature, they are the following ones [6].

$$V_d = V_\infty Sen\delta_r + r_e i_d - X_e i_q$$
$$V_q = V_\infty Cos\delta_r + r_e i_q + X_e i_d$$
$$V_T^2 = V_d^2 + V_q^2$$

The data of the system machine - infinite bus is shown in the Table 1. For the regulator of voltage ST1, these they are taken of the reference [6], likewise the data of the transmission line corresponds to a generator of 645 MVA in for unit [6].

Table 1. Data of the Low System Prove

ω_0	377	Xe	0.15
M	5.5294	re	0.01
Kd	3.0	KA	400.0
T’do	5.66	TA	0.02
T’’do	0.041	KF	0.008
T’’qo	0.065	TF	1.0
Xd	1.904	TX	0.025
X’d	0.312	P	0.824
X’’d	0.266	Xq	1.881
X’’q	0.260	Ra	0.0

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