International Journal of Engineering Research And Management (IJERM)
ISSN: 2349- 2058, Volume-08, Issue-03, March 2021

Design of a Neural Supervisor of Electrical Energy Production Units

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***Abstract*—This article discusses the creation of a supervisor to coordinate the operation of the energy production units connected to the interconnected power system. These production units are made up of Diesel power plants and hydroelectric power plants. We propose a supervisor system based on the artificial neural networks. In real-time, it provides the reference powers to the sources production according to the demand of electrical energy consumers. The results obtained, using the simulation, show that the supervisor's performance is satisfactory.**

***Index Terms*—Artificial neural networks (ANN) supervisor, hydropower plants, multivariable neural system, training algorithm**

I. INTRODUCTION

The region of DIANA has great potential in terms of renewable energy (wind, solar, hydraulic). We have studied the operation of hydropower plants (Andranomamofona, Ampandriambazaha and Bevory) of 77 MW in the interconnected power systems of this region. The idea was to size the high voltage power transmission lines that could link five districts in this region so as to supply them with electricity. The results obtained have shown us that the operation of the three hydropower plants will be able to operate for twenty nine years and the voltage levels of 220 kV and 90 kV are well suited to the operation of the interconnected power systems [1]. The interconnected power system the region of DIANA is illustrated in Fig.1. The region DIANA is located in the extreme north of the island of Madagascar (12° 16' South latitude, 49° 17' East longitude) [1].

Manuscript received March 12, 2021

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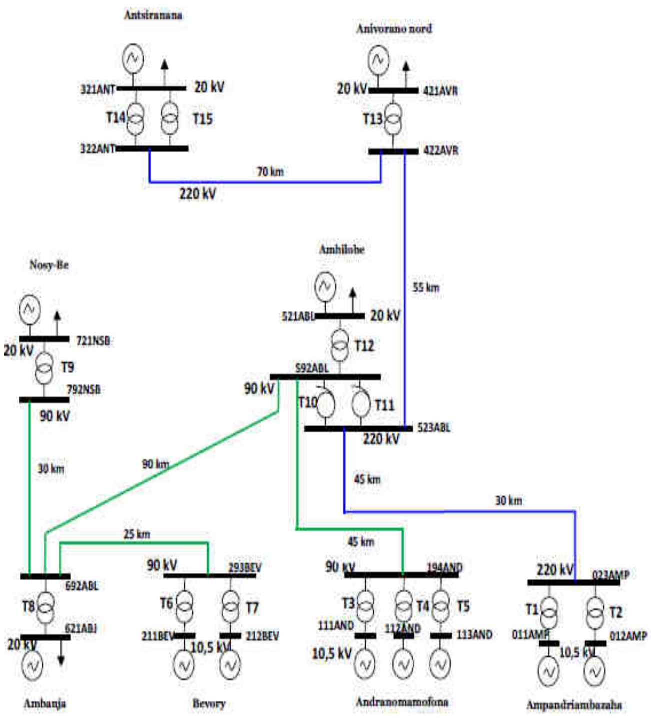

Fig.1: Interconnected power systems of the region DIANA

Several research works are proposed in the review of the literature concerning the supervision of hybrid (multisource) electric power generation systems based on fuzzy logic (FL) for more than decades. Lamine CHALAL dealt with the supervision of multi-source systems integrating renewable production resources [2] ; Vincent COURTECUISSE studied the real-time supervision of a multisource wind turbine based power plant associated with energy storage connected to the electrical power system [3] ; the work of Steve Perabi NGOFFE et al. concerned the optimization of an FL supervisor applied to the hybrid Photovoltaic-Diesel Generator system [4] ; Firas ALKHALIL dealt with the methodology of multi-level supervision of hybrid systems (gas microturbines and photovoltaic power plant) associated with the short-term storage system, connected to an electrical power systems [5] ; and in 2011, Mohamed NASSER proposed the supervision of wind-hydropower hybrid power generation sources in interconnected or isolated power systems [6]. In this article, the goal of our work is to create an Artificial Neural Network (ANN) supervisor. This supervisor sends control signals in the form of reference powers to the various energy production units.

II. FORMULATION OF THE PROBLEM

A. *Presentation of the electrical energy system*

Fig.2 shows the block diagram of the electrical energy system studied :

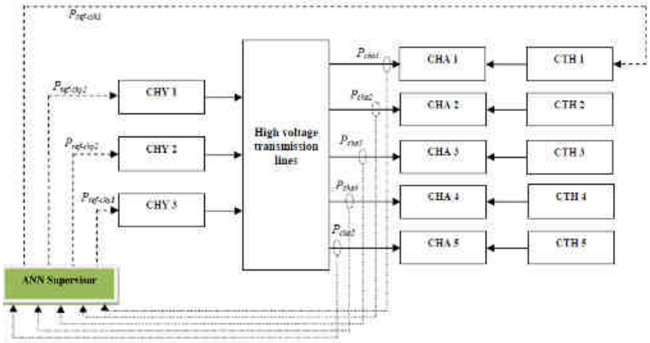

Fig.2 : Structure of the electrical energy system

This figure shows us the electrical energy system in interconnected mode. This mainly involves : - a central ANN supervisor ; - three hydropower plants (CHY i, with $i=\overline{1,3}$) ; - five Diesel power plants (CTH j, with $j=\overline{1,5}$) ; - high voltage transmission lines that transport the electrical energy produced ; - five loads (CHA k, with $k=\overline{1,5}$) which are supplied by Diesel power plants.

B. *Presentation of the ANN supervisor*

The central ANN supervisor manages the energy production units. It receives information on the load side such as the measured active powers. And at the same time, it gives the control signals in the form of reference powers for the hydropower plants as well as the Diesel power plant CTH 1. The ANN supervisor is a multivariable neural system.

Fig.3 : Neural system for the supervision of energy production units

The different variables of the neural system are :
- input variables : P_{cha1} represents the power measured at load n ° 1 ; P_{cha2} which is the power measured at the second load ; P_{cha3} the measured power of load n ° 3 ; P_{cha4} the power of the fourth load supplied by the CTH 4 plant ; P_{cha5} is the power measured at load n ° 5 ;
- output variables : $P_{ref\text{-}cth1}$ represents the reference power of the central CTH 1 ; $P_{ref\text{-}chy1}$ represents the reference power of the CHY 1 hydropower plant ; $P_{ref\text{-}chy2}$ is the reference power of the second CHY 2 control unit ; $P_{ref\text{-}chy3}$ is the reference power that drives CHY 3.

C. *Artificial neural network*

An artificial neural network (ANN) is a new means of processing information inspired by the functioning of biological neurons. By analogy with the electrochemical model of the biological neuron, the modeling of an artificial neuron is illustrated in the following figure :

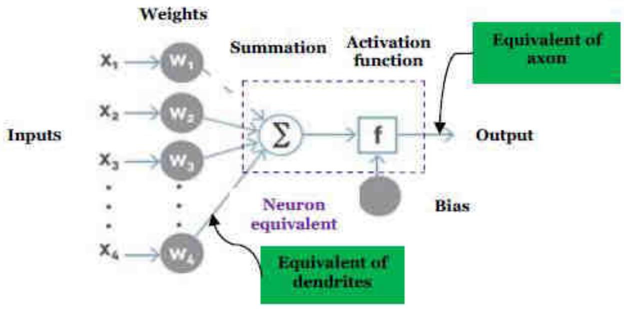

Fig.4 : Diagram of the model of an artificial neuron

The mathematical formula of the neuron output is given by [7]:

$$\text{Output} = f(x) \text{ with } x = \sum_{i=1}^{n} w_i . x_i + b \qquad (1)$$

where x is the activation state ; b is the neuron bias ; f is the activation function of the neuron ; w_i is the connection weight of the neuron.

We can solve the multivariable system for the multilayer perceptron neural network. In our case, we have the following three-layer neural network [7], [8] :

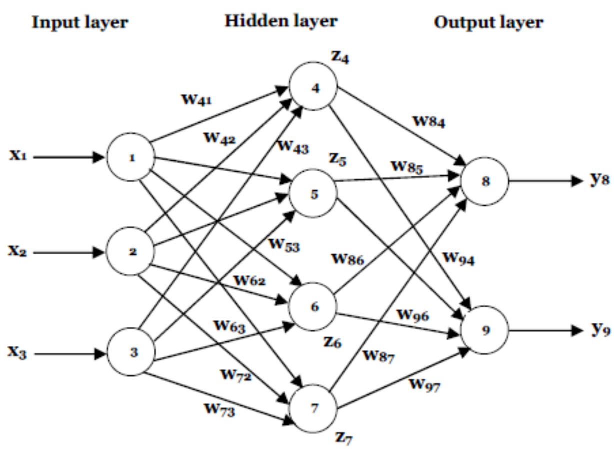

Fig.5 : Multilayer perceptron neural network

It is possible to define matrix relations that link the input vector x and the output vector y :

$$\begin{bmatrix} y_8 \\ y_9 \end{bmatrix} = \begin{bmatrix} w_{81} & w_{82} & w_{83} \\ w_{91} & w_{92} & w_{93} \end{bmatrix} . \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad (2)$$

with

$$W = \begin{bmatrix} w_{81} & w_{82} & w_{83} \\ w_{91} & w_{92} & w_{93} \end{bmatrix} = \begin{bmatrix} w_{84} & w_{85} & w_{86} & w_{87} \\ w_{94} & w_{95} & w_{96} & w_{97} \end{bmatrix} . \begin{bmatrix} w_{41} & w_{42} & w_{43} \\ w_{51} & w_{52} & w_{53} \\ w_{61} & w_{62} & w_{63} \\ w_{71} & w_{72} & w_{73} \end{bmatrix}$$

where w is the synaptic weight matrix.

D. *Training algorithm*

We used the multilayer perceptron neural network. Here is the step of the backpropagation algorithm :

Step 0 : Initialize the weights to small random values

Step 1 : Feed the training sample through the network and determine the final output

Step 2 : Compute the error for each output unit, for unit k it is :

$$\delta_k = (t_k - y_k).f'(y\_in_k) \qquad (3)$$

Step 3 : Calculate the weight correction term for each output unit, for unit k it is :

$$\Delta w_{jk} = \eta.\delta_k.z_j \qquad (4)$$

Step 4 : Propagate the delta terms (errors) back through the weights of the hidden units where the delta input for the jth hidden unit is :

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k.w_{jk} \qquad (5)$$

The delta term for the jth hidden unit is :

$$\delta_j = \delta\_in_j.f'(z\_in_j) \qquad (6)$$

where $f'(z\_in_j) = f(z\_in_j).[1 - f(z\_in_j)]$

Step 5 : Calculate the weight correction term for hidden unit :

$$\Delta w_{ij} = \eta.\delta_j.x_i \qquad (7)$$

Step 6 : Update the weights :

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \qquad (8)$$

Step 7 : Test for stopping (maximum cycles, small changes, etc…)

III. RESULTS

A. *Design of the ANN supervisor model*

The design of a neural model includes the following steps [9], [10] : - determining the inputs and outputs ; - collecting the data necessary for learning ; - determining the number of neurons in the hidden layers necessary to obtain a satisfactory approximation ; - carrying out the learning ; - evaluation of the performance of the neural network at the end of the training.

The input parameters of the ANN are based on the data of the evolution of the power of each district.

The output parameters of the ANN are the reference powers of the hydropower plants and that of the Diesel power plant supplying load n ° 1.

Thirty-seven (37) samples were taken into consideration.

The third step is to determine the number of neurons in the hidden layer, using the following relation [11] :

$$N_e \leq N_c \leq 2.N_e + 1 \qquad (9)$$

Table.1 below shows the choice of the number of neurons in the hidden layer after several learning tests.

Table.1 : Determination of the configuration of the ANN according to the number of neurons and the Mean Square Error (MSE)

Test number	Hidden layer	Number of neurons per hidden layer	Mean Square Error (MSE)
1	1	5	$4,74.10^{-8}$
2		6	$4,14.10^{-8}$
3		7	$2,99.10^{-8}$
4		8	$3,86.10^{-8}$
5		9	$3,28.10^{-8}$
6		10	$1,10.10^{-5}$
7		11	$6,58.10^{-8}$

Table.1 shows us that a number of seven neurons in the hidden layer is optimal because the value of the corresponding MSE is minimal compared to the other neurons, that is to say $2.99.10^{-8}$. Therefore, the size of the configuration of the ANN for the supervision of the power generation units is (5-7-4).

This ANN supervisor works like a black-box. So, it is final architecture can represent as follows :

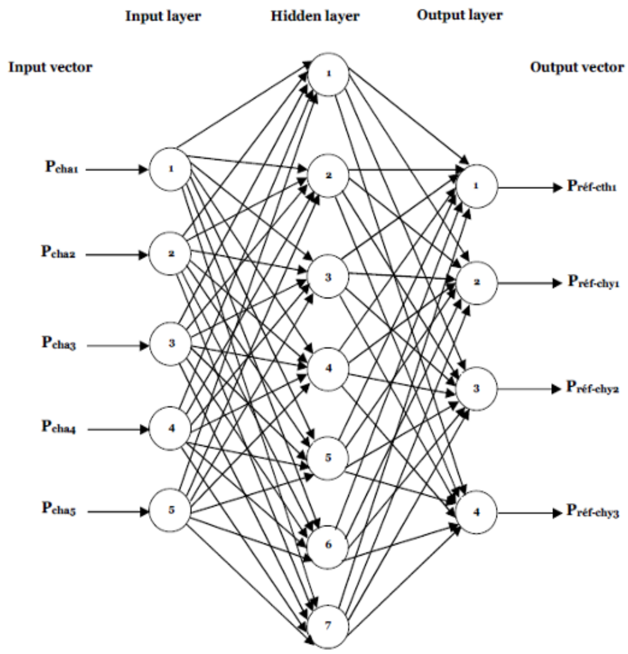

Fig.6 : Structure of the ANN with configuration (5-7-4) applied to supervision

This neural network, according to Fig.6, is made up of three layers, namely : - an input layer with five neurons represents the powers requested by the loads ; - a hidden layer with seven neurons with a linear activation function ; - an output layer with four neurons represents the reference powers for central power plants with a linear activation function.

The weight of the connection between neurons i and j is denoted w_{ij}. The ANN weights and biases for the hidden and output layers, during the learning phase, are shown in the following tables :

Table.2 : The weights and biases of the ANN (5-7-4) of the hidden layer

Input layer					
Weights					Bias
0.40387	0.26767	-1.6456	-3.0401	1.673	-4.4142
-2.3917	0.32065	0.17428	2.4882	-2.2562	2.3175
-1.4734	-1.5729	0.49858	3.0029	1.9801	0.71955
1.8011	0.15624	0.48728	1.7664	-2.508	-1.4539
-2.1433	2.551	-0.15727	-1.7802	0.82833	-1.4345
3.647	0.58257	-0.9607	-1.7537	0.18575	2.5543
1.2403	-0.10302	2.9052	-1.3523	1.564	4.3312

Table.3 : The weights and biases of the ANN (5-7-4) of the output layer

Output layer							
Weights							Bias
0.65334	-1.7564	0.96271	0.5644	-0.50942	0.55284	0.33403	0.19319
0.64245	-0.86678	0.90822	1.3067	-0.34197	0.055979	0.60316	7.3156
0.11478	-1.1687	0.87061	1.1213	0.14434	0.71095	0.34789	1.83071
-0.23051	-0.70809	0.67569	1.3652	-0.82996	0.71873	0.22537	1.48569

B. *ANN supervisor simulation*

Once the Artificial Neural Network is built and its training has reached satisfactory performance, we now move on to the testing stage. This test phase will take place in the Simulink environment. The architecture structure of the ANN (5-7-4) illustrated in Fig.6 can represent under the Simulink environment according to the following Fig.7 :

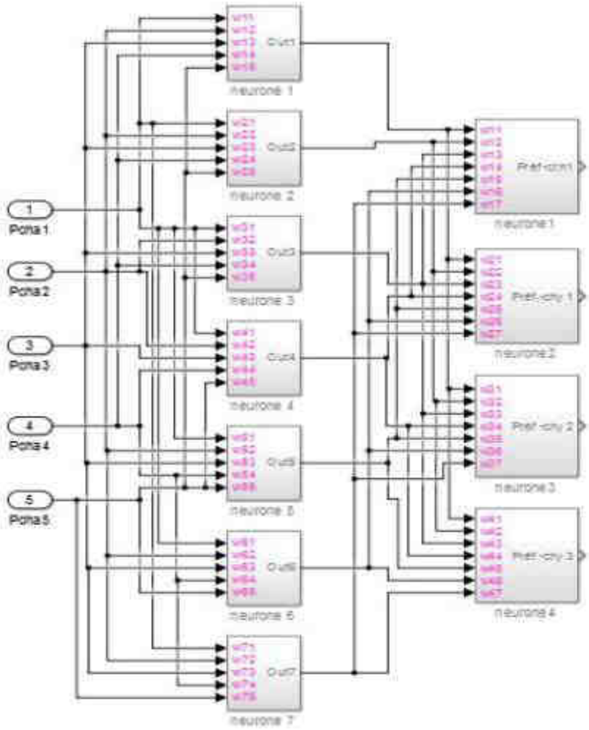

Fig.7 : Structure of the ANN supervisor in Simulink

The structure of the ANN supervisor consists of three parts : - the first part is the input to the neural network which represents the vector of active powers for the five different areas ; - the second part is the hidden layer with seven neurons. Each neuron constitutes five inputs and four outputs to connect to the output layer ; - the last part is the output layer with four neurons. This part allows communication to the external environment of the ANN supervisor.

The results of ANN supervisor simulations are shown in figures 8 (a) and (b). They have shown the load values at the inputs of the supervisor and the reference powers, at the outputs of this supervisor, for the central power plants.

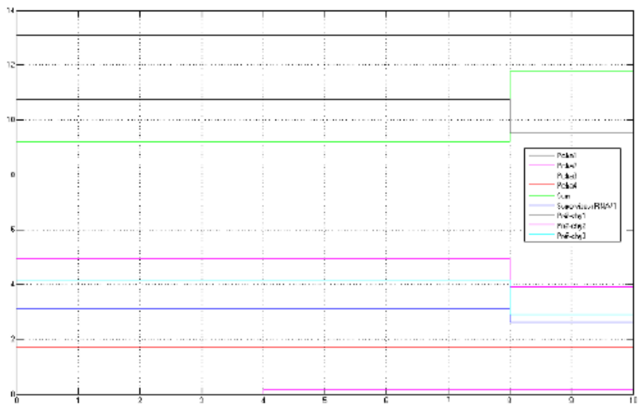

Fig.8 (a) : Evolution of the powers at the outputs of the ANN supervisor

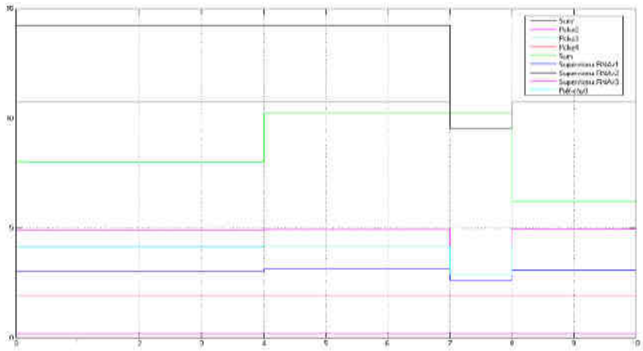

Fig.8 (b) : Evolution of the powers at the outputs of the ANN supervisor

Between 0 and 4 s, for Fig.8 (a), the powers at the ANN supervisor inputs are P_{cha1} = 13.110 MW; P_{cha3} = 1.426 MW; P_{cha4} = 1.725 MW; P_{cha5} = 9.200 MW. At the outputs of the supervisor, we have the following reference powers: $P_{réf\text{-}cth1}$ = 3.135 MW; $P_{ref\text{-}chy1}$ = 10.75 MW; $P_{ref\text{-}chy2}$ = 4.93 MW; $P_{ref\text{-}chy3}$ = 4.16 MW. Between 4 and 8 s, we introduce P_{cha2} = 0.159 MW but the others remain unchanged (P_{cha1} = 13.110 MW; P_{cha3} = 1.426 MW; P_{cha4} = 1.725 MW; P_{cha5} = 9.200 MW). At the outputs of the ANN supervisor, we have $P_{ref\text{-}cth1}$ = 3.135 MW; $P_{ref\text{-}chy1}$ = 10.75 MW; $P_{ref\text{-}chy2}$ = 4.93 MW; $P_{ref\text{-}chy3}$ = 4.16 MW. And finally between 8 and 10 s, the power of load 5 increased by 2.537 MW and the others remain unchanged (P_{cha1} = 13.110 MW; P_{cha2} = 0.159 MW; P_{cha3} = 1.426 MW; P_{cha4} = 1.725 MW). The power values at the outputs of the supervisor are $P_{ref\text{-}cth1}$ = 2.622 MW; $P_{ref\text{-}chy1}$ = 9.653 MW; $P_{ref\text{-}chy2}$ = 3.907 MW and $P_{ref\text{-}chy3}$ = 2.915 MW.
At t = 8 to 10 s for Fig.8 (b), the values at the supervisor's inputs are constant (P_{cha1} = 10 MW; P_{cha2} = 0.177 MW; P_{cha3} = 1.578 MW; P_{cha4} = 1.920 MW). But the power of load 5 dropped by 4 MW. Therefore, the latter becomes P_{cha5} = 6.240 MW. The results obtained at the outputs of the ANN supervisor are $P_{réf\text{-}cth1}$ = 3.054 MW; $P_{ref\text{-}chy1}$ = 10.713 MW; $P_{ref\text{-}chy2}$ = 4.963 MW and $P_{ref\text{-}chy3}$ = 4.262 MW.

IV. CONCLUSION

In this article, we have proposed a supervisor of electrical energy production units connected to high voltage electrical power systems. A methodology has been developed to build the supervision of this studied electrical system. This is based on a neural network supervisor. The performance of this supervisor has been shown using simulation in Simulink. The simulation results are satisfactory because the ANN supervisor can supply the reference powers. Future work will apply to the interconnected power systems of the region DIANA [1] in order to participate in secondary frequency control in automatic mode.

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