

Neuro-Fuzzy Energy Management Strategy (NFEMS) in DC Micro-Grids multiple sources (PV/SSE)

Alphousseyni Ndiaye¹ and Bigue Ngom¹

¹Research Team Energetic System and Efficiency, Alioune Diop University of Bambey, BP 30, Senegal.

Abstract

This work studies Energy Management Strategy (EMS) of a DC Micro-Grid (MG) based a Neuro-Fuzzy hybrid type Adaptive Neuro Fuzzy Inference System (ANFIS). The study system is composed a Photovoltaic Panels (PVP) - Storage System Energy (SSE)-DC Load and MG. The aim of this work is to propose a supervision algorithm based ANFIS which will allow us ensure good management while optimizing energy flow and protect batteries against overcharging and discharging deep. The PVP optimization is ensured by the Maximum Power Point Tracking (MPPT) type Perturbation and Observer (P&O) and a Proportional Integral (PI) regulator is used to correct the bus DC voltage. The reference voltage of the DC Bus is fixed at 50V. The results via matlab Simulink prove the efficiency of this supervision algorithm and also show that the DC link voltage remains constant at 50V. The management algorithm with the ANFIS command makes it possible to charge and discharge the battery whatever the weather conditions.

Keywords: EMS, PVP, ESS, ANFIS, DC MG.

1. Introduction

Energy has become a key factor in terms of competitiveness, it is the basis of development economic and social. Today, a large part of the world's energy production is provided by fossil fuels. The consumption of these sources gives rise to emissions of greenhouse gases and therefore an increase in pollution which has serious repercussions on the environment. The use of fuels which occupy the first place among the sources of energy for more than a century in the world, began to be replaced by renewable energy sources such as solar PV, solar thermal, wind power, biomass, hydroelectric, geothermal energy etc ... These renewable energy sources present significant advantages such as availability, freedom from pollution etc.

Senegal is well endowed in terms of renewable energy resource, more specific in the field of solar energy, it has excellent solar potential with an average net specific annual production of 1650kWh/kW c/year (theoretical annual production from of photovoltaic system normalized by peak kW) and an average daily global irradiation energy of 5,8 kWh/m²/year[1]. This energy comes from the direct transformation of part of solar radiation into electrical energy. This conversion is carried out through a so-called photovoltaic cell based on a phenomenon called the photovoltaic effect. In the literature there are two photovoltaic systems: the stand-alone PV system and the grid-connected PV system. The problematic of this subject results that the energy storage system has always encountered problems of charging and discharging the battery, sometimes in electrical installations one leaves the battery charged to exceed their threshold which can damage the battery, or even shorten their lifespan, so for an optimal management of energy at the level of energy demand, optimization, supervision and regulation techniques seem to be the solutions to solve this problem. On the other hand if a source is connected to a load, its operating point is the meeting point between the characteristic of the source and that of the load, the disadvantage is that the operating point can not to be the optimal point.

The cumulative capacity of PV systems installed in the world is 900 GW of which about 90 % is of the grid-connected type [2]. This observation shows that it is essential to concentrate the research in autonomous systems.

The objective of our work is to propose a supervision algorithm based on artificial intelligence of the Neuro-Fuzzy Energy Management Strategy (NFEMS) which will allow us ensure good management while optimizing the flow of energy and Protect batteries against overloads and deep discharges.

2. METHODOLOGY (NFEMS)

2.1. ANFIS Command

ANFIS (Adaptive Neuro-Fuzzy Inference System) is a Neuro Command Fuzzy Hybrid (NCFH) which combines the advantages of Artificial Neural Networks (ANN) and Fuzzy Logic (FL). Neuro-Fuzzy Systems (NFS) are applied in several fields of economics, health, chemicals, physics, etc.. and more precisely in photovoltaic systems. They are used to model, to control, to optimize, to predict weather conditions, to predict the power of photovoltaic panels and to supervise the energy flow. And within the framework of our work the (SNF) are used to make energy management. (NFS) are fuzzy systems formed by a learning algorithm inspired by the theory of neural networks and fuzzy logic [3]. The structure of fuzzy neural systems is given in “FIG.1”.

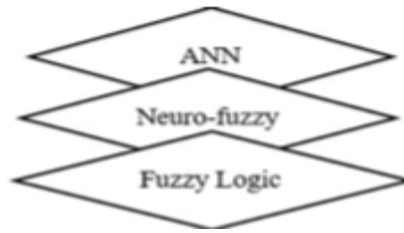


Fig. 1. Fuzzy neuro system

In general terms, the bibliography indicates that the NFS which implement the fuzzy inference systems of the Takagi-Sugeno type (TS) obtain more precise results than the one which implement Mamdani-type neurofluid inference systems [4]. And in our work, we use the Takagi-Sugeno-type neuro-Fuzzy system.

2.2. Architecture of ANFIS by Takagi-Sugeno

The Takagi Sugeno model has two inputs x_1 and x_2 and an exit f . Its structure is shows that it consists of five layers, each layer has different functions.

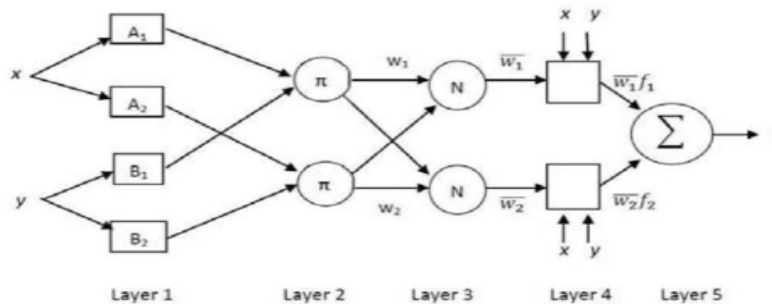


Fig. 2. ANFIS structure [5]

We are going to train a network that will allow us to tune our rules for each entry and give output weights corresponding to an optimal one. ANFIS puts in application a Takagi- Sugeno (TS) of the fuzzy inference system type and has five-layer architecture as shown in “FIG.2”.

The system under consideration consists of two inputs x and y and one output Y . The estimated TS fuzzy type model of the system has two rules:

$$\begin{cases} \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } Y = f_1(x, y) = A_1x + B_1y \\ \text{If } y \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } Y = f_1(x, y) = A_2x + B_1y \end{cases} \quad (1)$$

The nodes are either square or circular depending on their mode of operation. Square (adaptive) nodes contain parameters while circular nodes (fixes) do not. However, each (soft square) node applies a function to its input signals. The (soft square) node applies a function to its input signals. The O_i^k output of node i of layer k (called node (i, k)) depends on the signals coming from layer $k-1$ and on the parameters of node (i, k) , i.e:

$$O_i^k = f(O_1^{k-1} \dots O_{nk-1}^{k-1}, a, b, c \dots) \tag{2}$$

Where $nk-1$ is the number of the nodes in layer $k-1$ and a, b and $c \dots$ are the parameters of node (i, k)

Layer 1 FUZZIFICATION: The neurons in this layer make the fuzzy sets that will serve in the rule history. The membership functions are also found in the Jang model.

$$O_i^k = \mu_{Ai}(x) \tag{3}$$

Where x is the entry for node i and A_i is the linguistic term associated with its function. The parameters of a node of this layer are those of the corresponding membership function.

Layer 2 Fuzzy RULES: Each neuron in this layer corresponds to one rule of Sugeno-Takagi. It receives neuron outputs from fuzzification and calculates its activation as:

$$W_k = \mu_{Ai}(x) + \mu_{Aj}(y) \quad i = 1,2 \tag{4}$$

Where: k represents the rule number, i is the number of partitions of x , and j corresponds to the number of partitions of y .

Layer 3 NORMALIZATION: Each neuron calculates the normalized degree of truth of a given fuzzy rule. The obtained value represents the contribution of the fuzzy rule to the result firule

$$\varpi_i = \frac{W_1}{W_1 + W_2} \tag{5}$$

Layer 4 DEFUZZIFICATION: Each i neuron of this layer is connected to a normalization neuron corresponding to the initial inputs of the network. It calculates the weighted consequence of the rule.

$$O_i^k = \varpi_i \cdot f_i = \varpi(A_i(x) + B_i(x) + C_i)_j \tag{6}$$

$$i = 1,2$$

Where ϖ_i is the output of layer 3, A_i, B_i and C_i are the parameters corresponding to the i rule.

Layer 5 SUMMARY: This includes a single neuron that provides the output of ANFIS while calculating the sum of all the outputs of the neurons in defuzzification.

$$O_i^k = V = \sum \varpi_i \cdot f_i \tag{7}$$

2.3. Description of the ANFIS interface in matlab

This step consists of determining the steps to follow in order to make the learning process. In the literature there are several learning algorithms which are, gradient descent learning, Windrow-Hoff learning, Hebb’s rule, Korhonen learning and backpropagation learning of the gradient of the mistake. Our choice relates to the re-propagation method which consists in creating a database. This bass will be distributed as follows: 60 % data for training and 40 % data for verification. [7] [8].

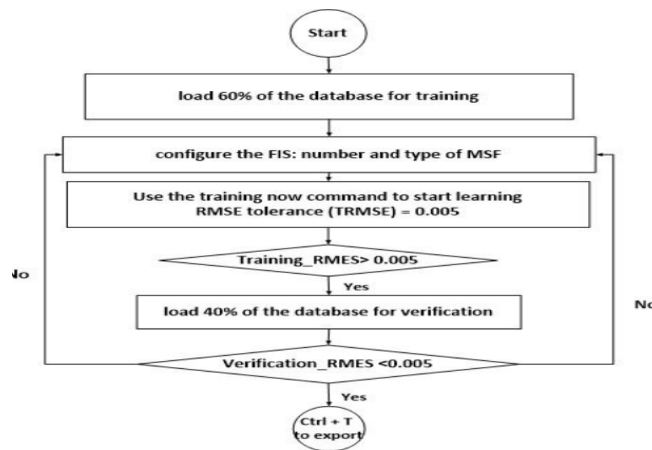
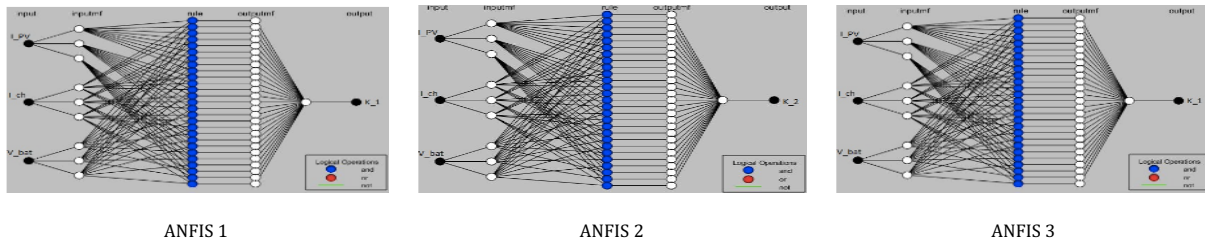


Fig 3. Diagram of the ANFIS learning procedure.

This is what we will follow in the rest of our work to learn.



The fuzzy rules of this learning are given in “FIG.4”.

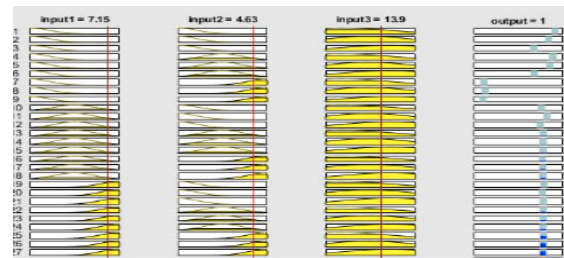


Fig. 4: Fuzzy rules

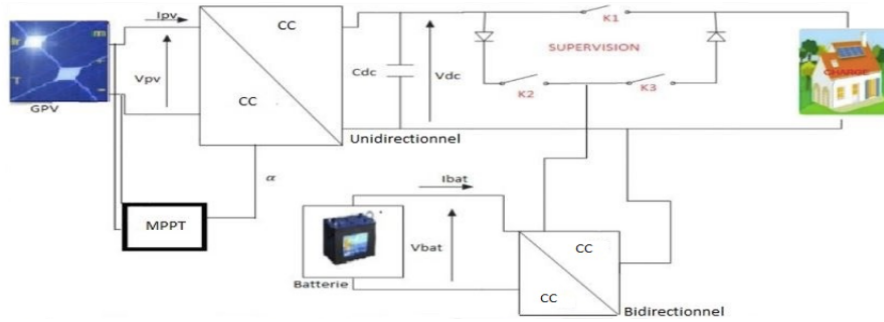


Fig. 5. Proposed supervision system for energy management in the system PV

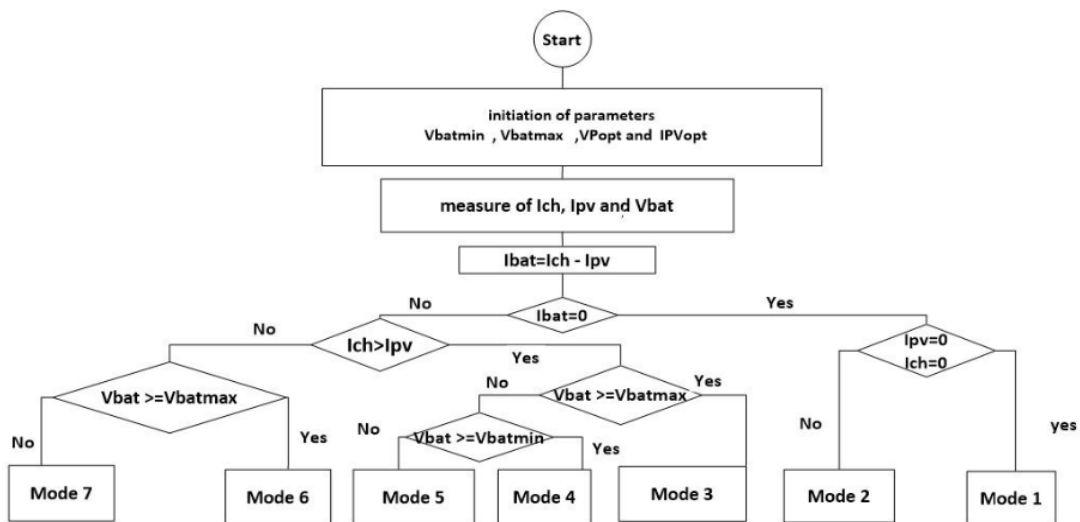


Fig.6. GPV / SSE / DC load supervision flowchart

The objective of this management is to ensure good management while optimizing the flow of energy, to charge/discharge the battery and to protect the battery against deep discharges and overloads. The battery current is calculated according to Eq.8.

$$I_{bat} = I_{load} - I_{pv} \quad (8)$$

We compare the load current (I_{load}) and that of the panel (I_{pv}) taking into account the state battery charge (SOC). Description of the various operating modes of the organization chart:

- Mode 1: If $I_{bat} = 0 \rightarrow I_{load} = I_{pv}$ (same value equal to zero) in this case, there is no photovoltaic production and the battery is completely discharged therefore the disconnection of the whole system is needed.
- Mode 2: Always $I_{bat} = 0 \rightarrow I_{load} = I_{pv}$ (same value different from zero) in this case, the battery must not be charged because its current is zero so the load is supplied by the photovoltaic generator.
- Mode 3: If $I_{load} > I_{pv}$ and the battery voltage is greater than or equal to 14.4 V in this case, the energy available by the photovoltaic generator is not sufficient to supply the charge, so the battery supplements the energy at the charge level. Compensation Mode.
- Mode 4: Always $I_{load} > I_{pv}$ and that the battery voltage is between 11.2 and 14.4 V in this case, mode 3 repeats.
- Mode 5: $I_{load} > I_{pv}$ and the battery voltage is less than 11.2 V in this case the panel charges the battery and the load will be disconnected.
- Mode 6: $I_{pv} > I_{load}$ and that the battery voltage is greater than or equal to 14.4 V in in this case, the panel produces enough energy to power the load and the battery will be disconnected to avoid overloads.
- Mode 7: $I_{pv} > I_{load}$ in this case, the energy available by the GPV is sufficient to supply charge and charge the battery. We present a table which allows us to analyze and study the different modes that we can distinguish during the operation of the presented system.

K1, K2 and K3 are respectively panel, battery and load switches.

3. RESULTS AND DISCUSSIONS

We will present the simulation results with the ANFIS command. The simulink model is given by “FIG.7”.

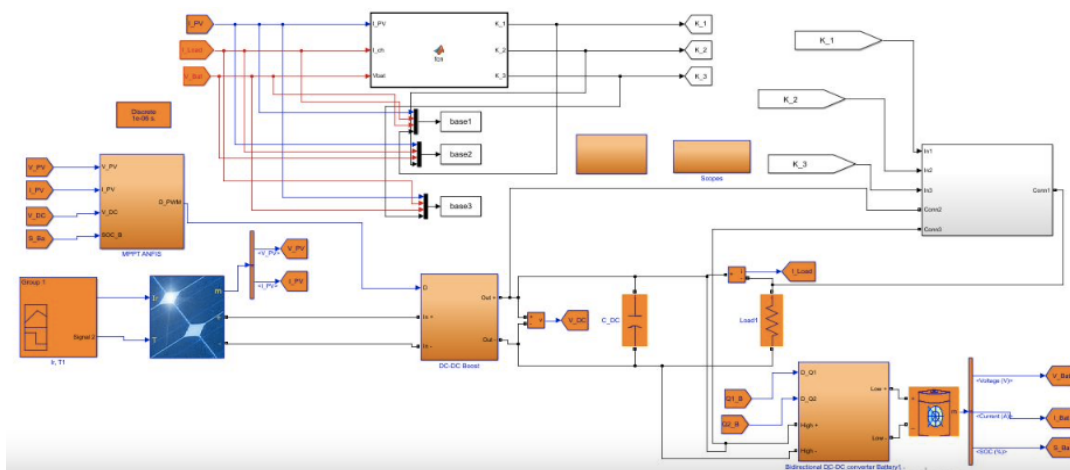


Fig. 7. Simulink model with the ANFIS command

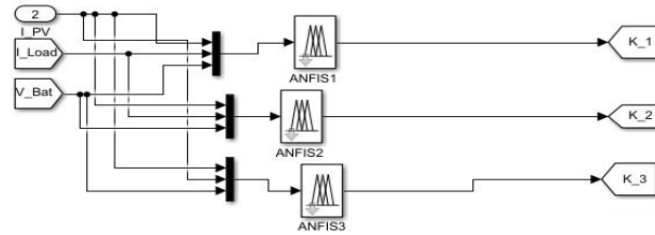


Fig. 8. Supervision with the ANFIS command

The characteristics of the battery are given by “FIG (9), (10) and (11)”.

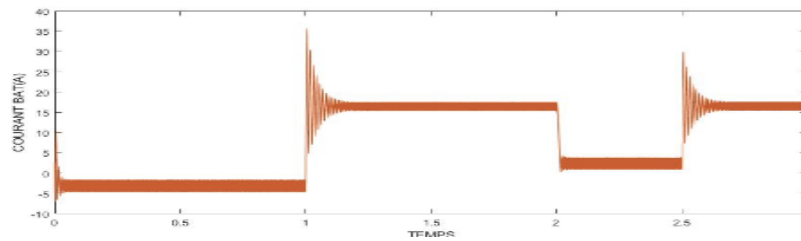


Fig. 9. Battery current

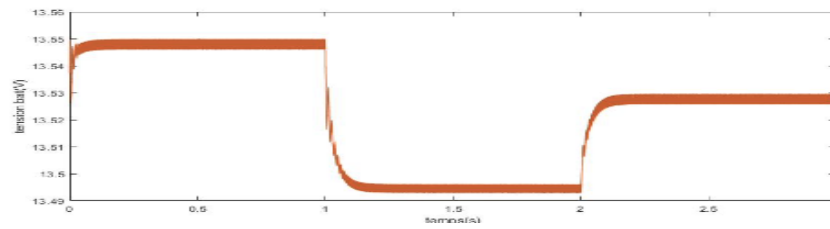


Fig. 10. Battery voltage

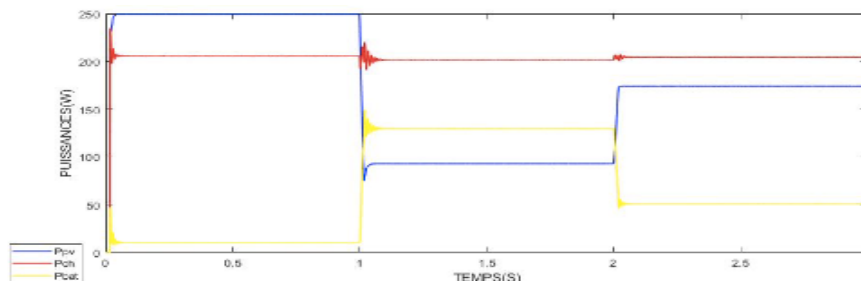


Fig. 10. Battery, PV and load powers

The state of charge of the battery is given in figure 11.

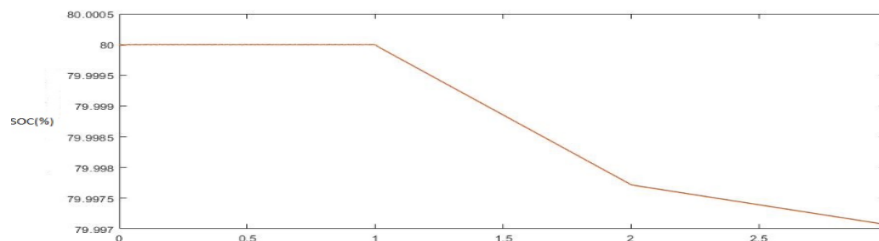


Fig. 11. Battery charge status with ANFIS

Figure 11 allowed us to deduce the various phases of operation of the supervision management algorithm: Phase 1: From [0 to 1 s], the GPV current is greater than the load current and the battery is charged, switch K2 disconnects the battery (K2 = 0) and the panel supplies the load (K1 = K3 = 1). During this time interval, the state of charge of the battery remains constant. Mode 6

Phase 2: From [1 to 2 s], during this step, the supervision management algorithm shows that if the load current is greater than the GPV current and the battery voltage is between the voltage minimum and maximum. Switches K1, K2 and K3 are in state 1. Mode 4

Phase 3: From [2 to 3 s], in this part the load current is always higher than the GPV current and the battery continues to discharge to supplement the energy at the load level. During this interval his SOC decreases. Switches K1, K2 and K3 are in state 1. Mode 3

The verification of the different operating modes allowed us to make a comparative study between the classical algorithm and the algorithm based on artificial intelligence. And we notice the technique based on artificial intelligence (ANFIS) is more efficient and more profitable.

IV. CONCLUSION

The work presented in this brief is the study of an energy management strategy for a hybrid DC micro-network (PV / SSE) based on neuro - blurry. The objective was to assure good management while optimizing energy flow and to protect the batteries against overloads and deep discharges. To do this, two commands were used. One of the P&O type to extract the maximum power from the photovoltaic generator whatever the weather conditions and the other of the ANFIS type to protect the battery against overloads and deep discharges.

REFERENCES

- [1] National Renewable Energy Action Plan (PANER) SENEGAL Period [2015-2020 / 2030].
- [2] T. K. Freddy, and Abd Rahim. Photovoltaic Inverter Topologies for Grid Integration Applications: Advances in Solar Photovoltaic Power Plants. Springer, Berlin Heidelberg, 2016.
- [3] F. Morgado and M. DIAS. Neuro-Fuzzy Systems, Escola Superior de Tecnologia de Setbal do Instituto Politecnico de Setbal, Departamento Electrotcnica, Campus do IPS, Estefanilha, 2914-508 Setbal, PORTU- GAL fmdias@est.ips.
- [4] YangWang,BeijingKeyLabofTrafficEngineering,BeijingUniversity of Technology, Beijing, Chine Courriel wangyang, 2014.
- [5] Zaini Abdul Halim and al, Adaptive Neuro-fuzzy Inference System as Cache Memory Replacement Policy, 2014.
- [6] JOS VIEIRA, FERNANDO MORGADO and ALEXANDRE MOTA. Neuro-Fuzzy Systems a Survey, Departamento de Eng Electrotcnica, Escola Superior de Tecnologia de Castelo Branco, Avenida do Empre- sario.
- [7] BottaandTango.EvaluationofDisctracktioninaDrive-Environnement Framework: An application of differennt data -mining technique, 2009.
- [8] Mukkamala and Janovski. Evaluation of Disctracktion in a drive - environnement Framework: An application of different data- mining tcehnique, 2002.