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Power interface efficiency evaluation for photovoltaic system used in hydrogen production

***Abstract**. In this work, we will compare between two types of converters Cuk and SEPIC because they are the most widely used and are two of the developed family of the converter. This paper presents under MATLAB/Simulink the use of CUK converter with maximum power point tracking (MPPT) technology, to increase its efficiency by an algorithm Perturb and Observe (P&O) and incremental conductance method, then we will apply artificial neural network (ANN) to avoid the disadvantages of MPPT Classical. The MPPT developed presents a better behavior than the P&O system*

Streszczenie.** W artykule porównano dwa rodzaje przekształtników CUK i SEPIC ponieważ są one najczęściej używane. Przedstawiono symulację użycia przekształtnika CUK w technice śledzenia punktu maksymalnej mocy MPPT oraz algorytmy Perturb and Observe (P&O) przyroostowej przewodności. **Poprawa jakości układu elektronicznego w systemie fotowoltaicznym użytym do produkcji wodoru

Keywords: Magneto Caloric Effect; Hydrogen; Maximum Power Point Tracking; Perturb and Observe; Artificial Neural Network.
Słowakluczowe: przekształtnikio CUK I SEPIC, System fotowoltaiczny,

Introduction

Magneto Caloric Effect (MCE) consists to liquefying hydrogen to optimize its storage,the hydrogen producedtoday by means of solar energy that become an important source of power generation. However, the main problem in the proper exploitation remain how it is stored; one of the best storage methods is the liquefied hydrogen system. The hydrogen generation system simply consists of a PV module that connected to a hydrogen cell by DC converter that means the best optimization of hydrogen system is optimization of the photovoltaic (PV) system.

A dozen of studies have been conducted on the use storage in renewable energy. Where Khalid *et al.* [1] suggested a renewable-based energy system for a house using hydrogen as a storage medium. Kalinci*et al*. [2] studied a standalone energy system for an island in Turkey using hydrogen as a storage option. ezmalinovic et al. [3] discussed the role of PEM fuel cells in PV based systems for remote base stations. They considered various scenarios such as PV/battery, PV/battery/diesel, generator and PV/battery/PEM fuel cell [4].

Electrolyzer cell technology provides a sustainable solution for renewable energy storage and hydrogen production. Among all types of electrolyzer cell systems, PEMFC is providing a promising solution for hydrogen and oxygen production and receiving more and more attention due to their higher energy efficiency/density, faster charging/discharging, and a more compact design [5].

Solar power is the conversion of sunlight into electricity, either directly using photovoltaic (PV), or indirectly using concentrated solar power. Concentrated solar power systems use lenses or mirrors and tracking systems to focus a large area of sunlight into a small beam. Photovoltaic cells convert light into an electric current using the photovoltaic effect [6].

PV solar systems exist in many different configurations with regard to their relationship to inverter systems, external grids, fuel cell, battery banks, or other electrical loads [7].

Regardless of the ultimate destination of the solar power, though, the central problem addressed by MPPT is that the efficiency of power transfer from the solar cell depends on both the amount of sunlight falling on the solar panels and the electrical characteristics of the load.

As the amount of sunlight varies, the load characteristic that gives the highest power transfer efficiency changes so that the efficiency of the system is optimized when the load characteristic changes to keep the power transfer at the highest efficiency. This load characteristic is called the maximum power point and MPPT is the process of finding this point and keeping the load characteristic there. Electrical circuits can be designed to present arbitrary loads to the photovoltaic cells and then convert the voltage, current, or frequency to suit other devices or systems, and MPPT solves the problem of choosing the best load to be presented to the cells in order to get the most usable power out.

This paper proposes the method to track the maximum power point (MPP) for a PV module using Perturb & Observe (P&O) based on artificial neural network (ANN) to optimization algorithm technique at varying irradiation and temperature. There is in the literature many definitions, of Artificial Neural Networks, regardless of the mathematical definitions the Artificial Neural Networks are inspired by biological Networks. The Artificial Neural Networks can be modified topology of their own learning, which is defined as modifying synaptic weights to capture information [8].

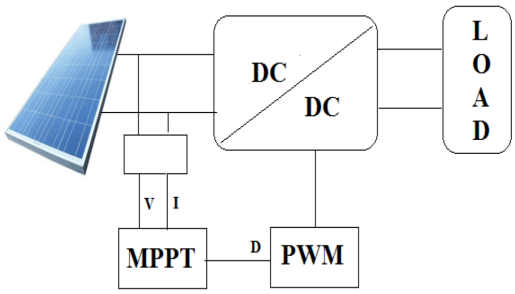

Fig. 1. Photovoltaic system

The DC-DC converter based photovoltaic (PV) energy system is applied in various convenient applications. There are several different types of dc-dc converters, buck, boost, buck-boost and Cuk topologies, have been developed and reported in the literature to meet a variety of application specific demands. One advantage of these converters is its high-power efficiency. Higher order dc-dc converters, such as the Cuk converter, have a significant advantage over other inverting topologies since they enable low voltage ripple on both the input and the output sides of the converter [9].The concept consists, in fact, of producing hydrogen from the photovoltaic effect, which will then be liquefied by magneto-caloric effect in situ, focusing to manage and to achieve out an efficient and embedded magnetocaloric devices for low temperature and space applications.

Description of the PV system

Thousands of PV systems are used today for a variety of applications, Figure 1 shows the studied PV system which includes the PV array, converters with different MPPT algorithms, which it will be replaced later by ANN based P&O algorithms

Analytic photovoltaic models

An ideal Photovoltaic cell consists of a single diode connected in parallel with a light generated current source, *Iph* (Figure. 2a), where, its output current *I* can be written as [10].

$$I = I_{Ph} - I_S\left[e^{\frac{V}{nV_t}} - 1\right] \quad (1)$$

where: *Is*: cell saturation of dark current; V_t: thermal voltage $V_t = kTc/q$; k: Boltzmann's constant, = 1.38 • 10-23 J/K; *Tc*: cell's working temperature; *q*: electron charge (1.6 • 10^{-19}C). *n*: ideality factor equal to 1.1.

Non-Ideal Photovoltaic Models

There are two types of non-ideal first model with series resistance (*Rs*-model) is shown in the Figure 2b and is annotated by equation (2) of the output current.

$$I = I_{Ph} - I_S\left[e^{\frac{V+IR_S}{nV_t}} - 1\right] \quad (2)$$

Nevertheless, this model does not adequately represent the behavior of the cell, for that there is another model where series Rs, and parallel resistances Rsh, are introduced [11]. Series resistance is very small. It has shown in Figure. 2c and its equation as:

$$I = I_{Ph} - I_S\left[e^{\frac{V+IR_S}{nV_t}} - 1\right] - \left[\frac{V+IR_S}{R_{sh}}\right] \quad (3)$$

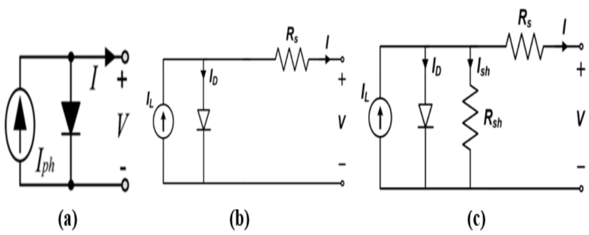

Fig. 2. Circuits model for PV cell

Design of dc-dc converter

The Cuk converter contains inductors in series with the converter input and output ports. The switch network alternately connects a capacitor to the input and output inductors. It can be modeled by the equations relating input and output voltage/current as follows [11]:

$$V_{out} = \left[\frac{-DV_{in}}{1-D}\right] \quad (4)$$

$$I_{out} = \left[\frac{(1-D)I_{in}}{D}\right] \quad (5)$$

With Cuk converter, we can operate with smaller or larger dimensions than the input voltage. However, there is a disadvantage with regard to the inversion of the output voltage sign to that of the input voltage.

The single-ended primary inductance converter (SEPIC) can also either increase or decrease the voltage magnitude. However, it does not invert the polarity. The conversion ratio is:

$$M(D) = \frac{D}{1-D} \quad (6)$$

MPPT methods

Two of the most widely used methods for maximum power point tracking are studied here. The methods are [12]:

- Perturb & Observe Method.
- Incremental Conductance Method.

The flow charts for the two methods are shown below in figures 3 and 4.

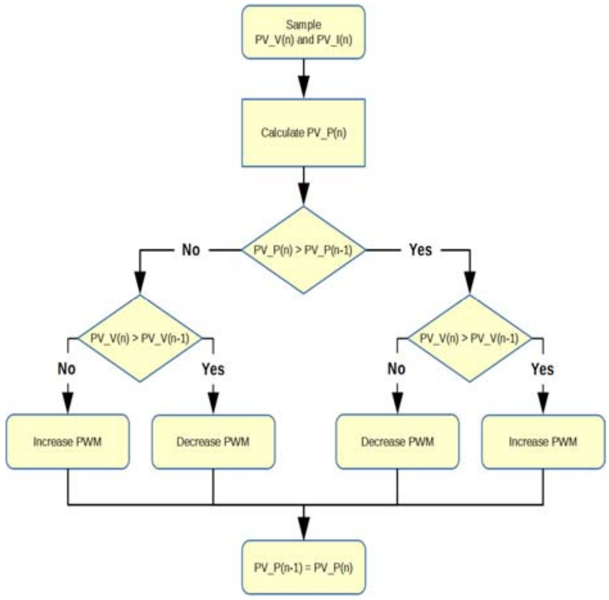

Fig. 3. Perturb & Observe Method

The operation of this algorithm is as follows:

First, the voltage V(n) and the current I(n) are measured to calculate the power P(n). This value P(n) is compared with the value of the power obtained during the last measurement P(n-1).With the help of this algorithm, the operating voltage V(n) is disturbed at each cycle. As soon as the MPP is reached, V(n) will oscillate around the ideal operating point (Vmp).

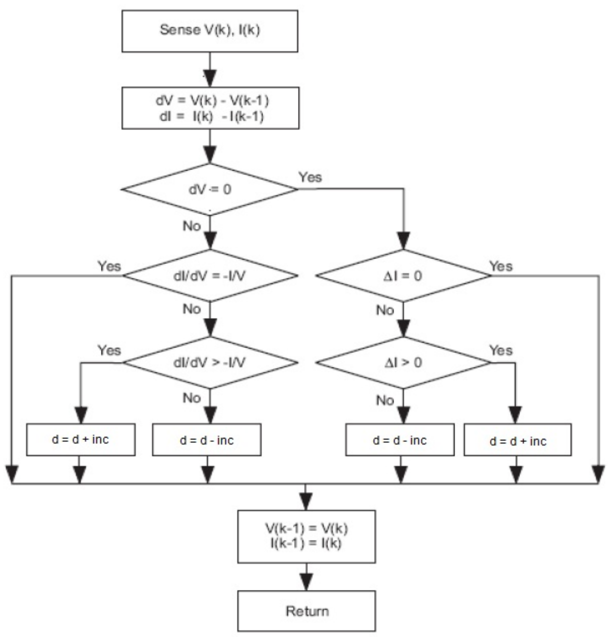

Fig. 4. Incremental Conductance Method

But this causes losses of powers which depend on the width of the pitch of a simple perturbationDD.If the step width is large, the P&O algorithm will respond quickly to sudden and rapid changes in operating conditions but will cause losses in slowly changing conditions and in stable states.If the width of the step is very small the losses in stable states or slowly changing conditions will be reduced, but the system will have a slow response to rapid changes in temperature or intensity of sunshine.

This method exploits the assumption of theratio of change in output conductance is equal to the negative output Conductance Instantaneousconductance.The MPPT regulates the PWM controlsignal of the dc – to – dc boost converter until the condition: (dI/dV) + (I/V) = 0 is satisfied.

In this method, the peak power of the modulelies at above 98% of its incremental conductance.

Electrolyzer system

An electrolyzer is an electrochemical device, which decompose water into hydrogen and oxygen. The production rate of H_2 in an electrolyzer cell is directly proportional to the transfer rate of electrons at the electrodes, which in turn equivalent to the electrical current in the circuit, as expressed in equation (7), and the ratio between the actual and the theoretical maximum amount of H_2 produced in electrolyzer is known as Faraday efficiency, which is also expressed in Eq. (7) as, [13].

(7) $$m_{H_2} = \frac{n_F N_{i_e}}{2F} \text{and} n_F = 96.5\left(e^{\frac{0.09}{i_e} - \frac{75.5}{i_e^2}}\right)$$

Hydrogen storage tank

The dynamics of H_2 storage tank system can be expressed in equation (8).

(8) $$P_b - P_{bi} = \frac{Z N_{H_2} R T_b}{m_{H_2} V_b}$$

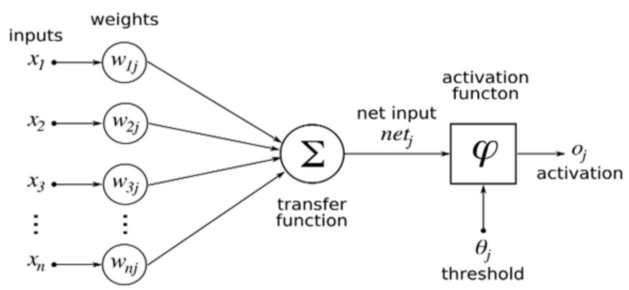

Fig. 5. The formal neuron architecture

Artificial Neural Network

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is an artificial neuron, that is, a simple mathematical model (function).

Such a model has three simple sets of rules: multiplication, summation, and activation. At the entrance of artificial neuron, the inputs are weighted what means that every input value is multiplied by individual weight.

In the middle section of the artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron, the sum of previously weighted inputs and bias is passing through activation function that is also called transfer function (Figure 5).

Training of Neural Networks

The neural network is selected having three layers one is hidden. The transfer function is used for hidden layers and by using back propagation method the network is trained using the data obtained, which it's measurement voltage and current of PV panel are being used as the input of ANN, the output is the duty cycle of the pulse width modulation (PWM), and its change to match the maximum power point. Neural networks are also often used for time series forecast [14].

The topology of NN consists of layers with neurons. An example of ANN is presented in Figure 5. The network has at least 3 layers: the input layer, one hidden layer, and the output layer. A number of hidden layers is varying and depends on design influenced by solving the problem. Neurons between layers are fully connected by weighted connections.

It means that each neuron in lower layer has the connection with each neuron in the upper layer. The process of feed-forward propagation of signal through NN begins with neurons excitation in input layer. Then these excitations are brought to the next layer. Each neuron of next layer proceeds summation of signals xi altered by connection weight w_i for each neuron *i* of n neurons from the previous layer showed in equation (9) [15].

(9) $$z = \sum_i^n w_i x_i$$

Output from this neuron is computed by its sigmoid activation function presented in equation (10):

(10) $$y = \frac{1}{1+e^{-\lambda z}}$$

Where λ is the slope of the sigmoid function. These signals are propagated to output layer through all hidden layers by presented way and outputs from NN are excitations of output neurons. Feed Forward Neural Network learning is processed by updating connection weights between neurons. It is necessary to learn NN using training set of knowledges.

Updating of weights based on training set is called Supervised Learning. One of the methods that allow NN adaptation on given training set is called Backpropagation.

Backpropagation (BP) algorithm is based on gradient descent method. Adaptation of weights is processed by propagation of outputs error back through the network from upper layers to lower layers. The goal is to minimize error function, see following equation (11):

(11) $$E = \frac{1}{2}\sum_{p=1}^{p}\sum_{j=1}^{M}\left(y_i - d_j\right)_p^2$$

Where error between real output from network yj and desired output *dj* is summed for *P* patterns of training set and for all m output neurons in output layer. Error minimization is done by adapting weights between neurons. Change of weight is done by equation (12):

(12) $$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}}$$

where η is learning coefficient. Then partial derivation of error *E* based on connection weight *wij* is obtained by equation (13):

(13) $$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial y}\frac{\partial y}{\partial z}\frac{\partial z}{\partial w_{ij}}$$

Based on equations (9) and (10), previous equation is simplified by equation (14) as:

(14) $$\frac{\partial z}{\partial w_{ij}} = \frac{x_i \wedge \partial y}{\partial z} = y(1-y)\lambda$$

Then gradient of neuron from equation (13) is transformed to equation (15):

$$\frac{\partial E}{\partial w_{ij}} = \delta_j y_j (1 - y_j) \lambda x_i \tag{15}$$

Where δ j is obtained from equation (16) for output layer:

$$\delta_j = y_j - d_j \tag{16}$$

And from equation (17) for hidden layer results

$$\delta_j = \sum_{i=0}^{m} \delta_j y_j (1 - y_j) \lambda w_{ij} \tag{17}$$

Simulation of PV system

The PV system presented in the figures 6, 7 and 8 is evaluated by a numerical simulation using MATLAB/Simulink tool, in which the PV systems inject active energy load by two converters Cuk and SEPIC with algorithm p of MPPT.

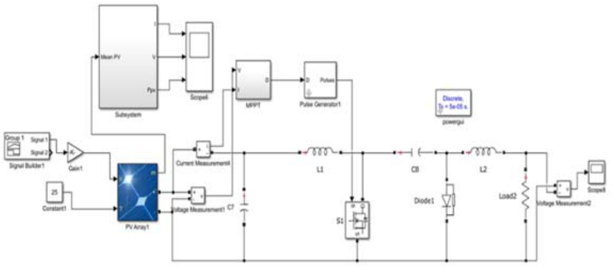

Fig.6. Cuk converter with MPPT

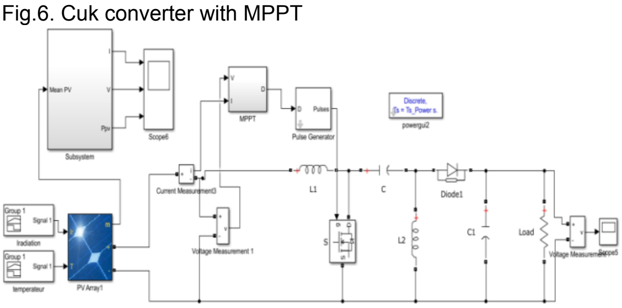

Fig.7. SEPIC converter with MPPT

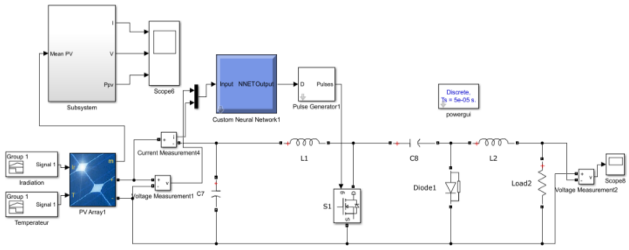

Fig. 8. Cuk converter with ANN

Discussion and comments

In this paper, there are two types of converter analyzed, developed and simulated using the MATLAB/Simulink, and they are connected to panel solar by the MPPT with algorithm P&O, and this in order to identify the best among them in the various levels of irradiation.

After this, we will compare classical algorithm with the artificial network, which is one of the intelligent techniques. In the final resort, we will reach to the best solar system for a better hydrogen production, which allows us to stores that improved exploitation of solar energy.

Comparison between Cuk converter and SEPIC

Figure 9 shows the result of a simulation model of the PV system used in this study, both of two types of converter. Where we note the Cuk converter it exhibits superior characteristics respecting the performance of PV array is MPPT.

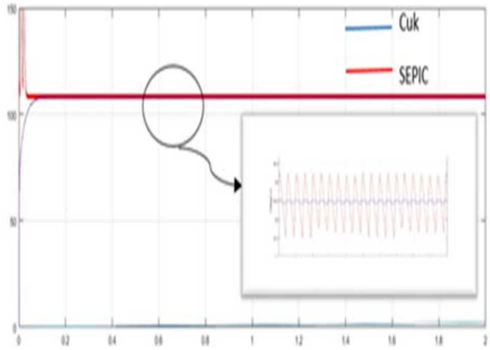

Fig.9. Comparison of the Cuk converter and the SEPICE for output voltage

Comparison between ANN control and P&O algorithm

Figures 10 to 12 show the results of comparison between ANN and P&O. From these figures, we conclude that Artificial Neural Network technology is more effective than an algorithm P&O, and has great speed in response regardless of the solar level, the array temperature, and the connected load.

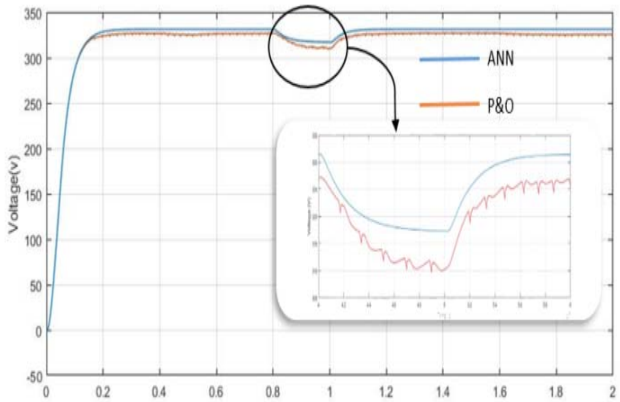

Fig.10. Comparison between Artificial Neural Network and P&O for output voltage

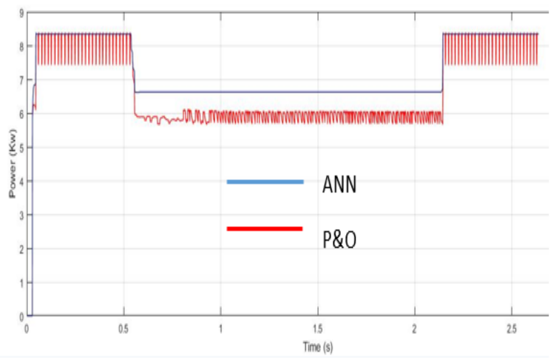

Fig. 11. Power PV for two methods Artificial Neural Network and P&O

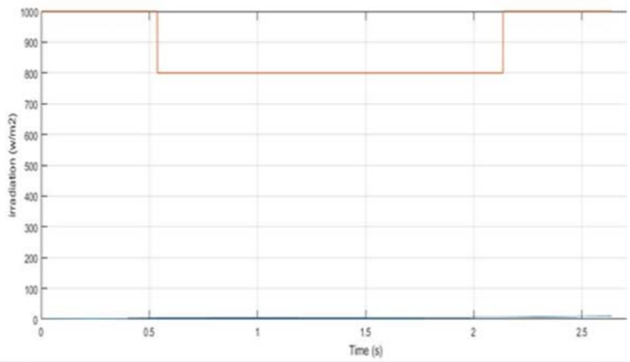

Fig. 12. Irradiations input

Conclusions

This paper presented a comparative study between two types of components of the solar system to produce hydrogen, for to increase the effectiveness of the system. However, changed some parts of the system, not enough to improve the system. Therefore, it has evaluated various known control techniques in literature to take advantage as much as possible of the available energy by a solar panel. In addition, to avoid the disadvantages of the classical methods has been replaced with the artificial intelligence technology, that gave an excellent result in terms of speed response and the amount of energy produced, which leads to raising the performance of the hydrogen production.

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