Maximum power point tracking using neural networks for stand-alone photovoltaic system

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Abstract— **the optimization of the photovoltaic (PV) system performance is done through the energy management stage. The first step of the optimization consists in extracting the maximum power available from the PV generator. This is done by the Maximum Power Point Tracking (MPPT) of the PV generator which varies with the irradiance, the temperature and the load. Several techniques as the 'Perturbation and observation' (P&O), the 'Incremental conductance' (INC), the 'Power feed-back method', the 'Hill climbing' are used for this tracking.**

In this article, we present a new MPPT algorithm, based on neural network controller (NNC), whose structure configuration is of three layer; an input layer, an output layer and a hidden layer. In order to show the functionality of the developed neural controller algorithm, we have applied it to a standalone PV system for several conditions of irradiance and temperature. The tests conducted on this NNC show that it allows the system to reach quickly the optimal performance with a stable pattern for all the cases considered.

Keywords- ***PV system; Maximum Power Point Tracking (MPPT); Neural Network; Neural Network Controller***

I. INTRODUCTION

A photovoltaic generator (PVG) consists of a number of solar cells connected in series and in parallel depending on the required power, voltage and current ratings. Although their prices are decreasing, PVG systems still require expensive investments. Therefore, it is very important to extract as much energy as possible from a PVG system.

Since the operating point of a PVG-load system depends on the load, the irradiance and the temperature, the PV system must be managed so that it must operates at its maximum power point in order to be used efficiently.

Several algorithms are used to optimize the power supplied by the PVG. The simplest maximum power tracking algorithm is to operate the PVG under constant voltage reference and to use a step up or down type DC–DC converter which keeps the PVG voltage constant.

The Perturbation and observation (P@O) method is another algorithm which is used for the maximum power tracking. It is based on a periodic perturbation of the operating point and the observation of change in power. Although it is a well established algorithm, some confusions and instabilities may occur when the irradiation and (or) load changes rapidly and randomly [1-3]. Two decades ago, a new generation of tools based on Artificial Intelligence was used in the MPPT algorithms, such as neural network and fuzzy logic which work with imprecise inputs, do not need an accurate mathematical model and handle nonlinearities [4-7]. Thanks to their efficiency and robustness, Neural Network (NN) algorithms have been widely applied in the MPPT [8-10].

In this article, we present a intelligent MPPT controller, based on neural network algorithm which is applied to a standalone PV system.

The paper is organized as follows: Next section describes the artificial neural network modeling. Section 3 provides development procedure for a proposed MPPT-NNC. The simulation results obtained by the developed MPPT neural controller for several operating conditions of irradiance and temperature under Simulink-matlab environment is outlined in section 4. Finally, conclusions and future action are drawn in section 5.

II. ARTIFICIAL NEURAL NETWORK MODELLING

Artificial neural networks are densely interconnected processing units that utilize parallel computation algorithms. Neural networks (NN) are composed of simple elements operating in parallel. These elements are inspired by biological nervous system, and the network functionality is determined by the connection between them [11].

Basically, the processing elements of an artificial neural network are analogous to the brain neurons, which consist of many simple computational elements arranged in several layers [12]. An artificial neuron is composed of many parts. The input values are external stimuli from the environment or come from the outputs of other artificial neurons. The first thing an artificial neuron does is to compute the weighted sum of its inputs; the weights are real-valued numbers that determine the contribution of each input. The synaptic weight is changed by using a learning rule. Summation function is a function that calculates the effect of inputs and weights completely on this process element. The weighted sums of the input components net_i are calculated using (1) as follows:

$$net_i = \sum_{j=1}^{n} W_{ij} x_i \qquad (1)$$

Activation function defines the properties of artificial neuron and can be any mathematical function. In general, we choose it from the following set of functions: Step function, linear function and Non-linear (Sigmoid) function. The output value (2) is calculated applying an activation function:

$$y_i = f(net_j) \qquad (2)$$

III. Development procedure for a PROPOSED MPPT neural controller

The proposed NNC is used to determine the optimum duty cycle Dopt which corresponds to the maximum power Pmax at any given solar irradiation S and PV cell temperature T. The elaboration of an MPPT controller based on neural network goes though several steps as indicated in Fig. 1.

A. Constitution of the database

The voltage and current of the PV module are measured instantaneously by A/N converter, and the power is calculated as follows:

$$P(n) = i(n).v(n) \qquad (3)$$

The two inputs of the proposed NNC are the tracking error (E) and the change of the error (ΔE), which are defined as [13, 14]:

$$E(n) = \frac{P(n) - P(n-1)}{V(n) - V(n-1)} \qquad (4)$$

$$\Delta E(n) = E(n) - E(n-1) \qquad (5)$$

Where n is the sampling time, P(n) is the instant power of the PV module and V(n) is the instant corresponding voltage. These inputs are chosen so that the instant value of *E (n)* shows the load operation power point location, while ΔE (n) expresses the moving direction of this operation point. The output variable is the duty cycle D generated in the pulse width modulation (PWM) signal form applied to the power MOSFET of the DC-DC converter usually used as a switching device since it is easy to control and can be operated at high frequencies. The power flow is thus controlled by varying the on/off duty cycle D of the switching period [13].

The transmitted control signal D to the DC/DC converter drives the load in order to track the maximum power of the PV module. The inputs and output values along with their ranges have been summarized in Table 1.

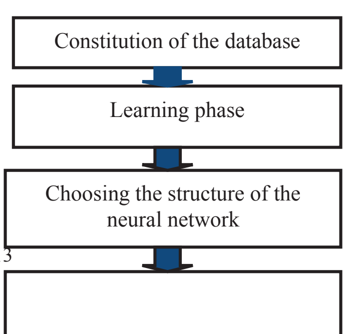

Fig.1. Development procedure for the proposed NNC

TABLE 1 The range of the input and output parameters in ANN model

Parameters	Min	Max	Mean	Standard deviation
E	-0.032	0.032	9.6774e-06	0.0222
Delta E	-100	100	7.4487	71.1760
D	0.45	0.6	0.5099	0.0128

B. The choice of the neural network structure

The second step in the development of the proposed controller◆ is the choice of the network structure. The number of inputs and outputs is generally imposed by the approximating function. In order to find an optimal configuration of the NNC, we have experienced several structures depending on the number of layers, the number of the neurons by layers and parameters as weights and activation functions.

At last, we have reached the following optimal configuration:

- The input layer is composed of two neurons corresponding to the two input variables *E* and *ΔE*.
- The hidden layer is composed of 5 neurons whose activation functions are tangential sigmoid.
- The output layer with one neuron representing the control signal "D" with a linear activation function.

The number of neurons in the hidden layer was empirically optimized during the training phase. Indeed, the many tests conducted have shown that the most stable structure is composed of five neurons. It should also be noted that the choice of the hidden layer activation function has not been adopted arbitrarily, but was chosen after several tests that showed that the tangential sigmoid function converges faster compared to the exponential sigmoid function during the training stage. Fig. 2 shows the proposed NN architecture for the MPPT-control and Fig. 3 presents the internal structure of the first and the hidden layers of the proposed NN model in Simulink.

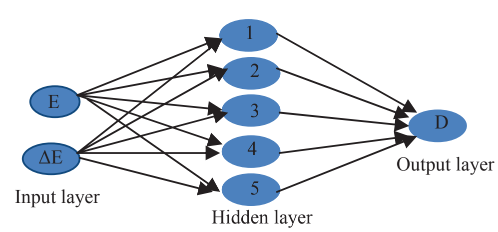

Fig. 2. Neural network architecture proposed for the MPPT control

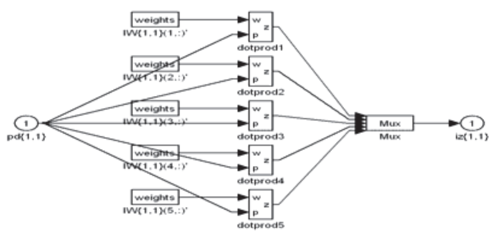

Fig. 3. Internal structure of the first and hidden layers of the proposed NNC

C. *Training phase*

This step concerns the training process of the neuron using an appropriate algorithm. Many ANNs algorithms were used in literature such as the unsupervised Kohonen algorithm [15] and the Hopfield one [16]. Among algorithms that adjust the process weights, back-propagation algorithm is the most widely used; the weights of the network are iteratively trained with the errors propagated back from the output layer [17]. The training process was done using a supervised training based on the back-propagation algorithm. Two factors must be optimized: the number of epochs which represent the training time, and the training performance which is the minimum mean square error (MSE) between the network outputs and the target outputs. During this step, the back propagation algorithm looks for the weights W_i which minimize the mean square error (MSE) governed by the following equation:

$$MSE = \frac{1}{2}\sum (D_{desired} - D_{estimed})^2 \quad (6)$$

Where $D_{desired}$ is the target value, and $D_{estimed}$ is the output value.

In other words, during the training, the weights of the network are continuously modified as long as the MSE error greater than a certain threshold value corresponding to a suitable accuracy. The aim is to find the weights that lead to the convergence of the target value. Once the training finished (minimum mean square error is achieved) the weights are no more modified, which correspond to the optimal NN structure. The training curve for the proposed NN architecture presented in Fig. 2 is demonstrated on Fig. 4 showing convergence to the target MSE of $8.053*10^{-6}$ after 205 iterations.

D. *The MPPT neural controller in PV system*

For each cycle of the control algorithm, a measure of the network input variables (E) and (ΔE) are performed then the generated duty cycle (D) is used by the DC/DC converter to maintain the system working in his MPP. This is done through the propagation of these data by the neural network. The NNC inserted in the PV system is shown in Fig. 5.

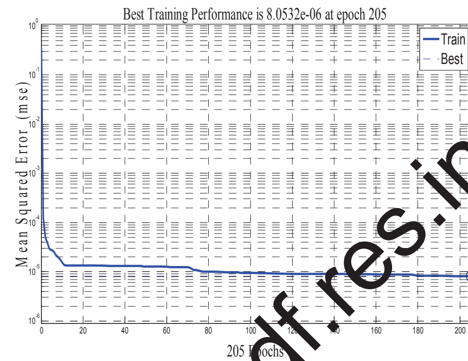

Fig. 4. Training curve for the proposed NNC

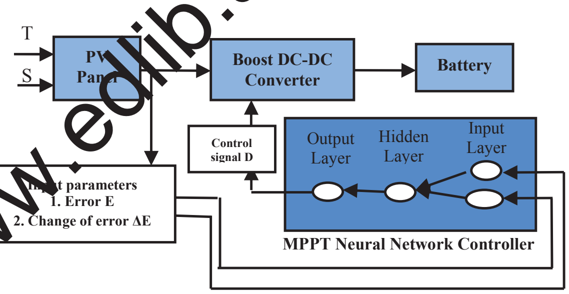

Fig. 5. Synoptic of the MPPT neural controller

IV. SIMULATION RESULTS OF MPPT NEURAL CONTROLLER APPLIED TO STAND-ALONE PV SYSTEM

In order to test the performance of the developed NNC, we have treated the case of a Stand Alone PV system composed by a generator (module of 36 cells, P=60Wp), the MPPT controller, a boost DC-DC converter and a lead- acid battery of 12V [18, 19].The implementation of this PV system with the proposed NNC under Matlab/Simulink environment is shown on the Fig. 6. Two kinds of tests were conducted (constant and varying S and T) to demonstrate the ability of the developed MPPT controller to react quickly and efficiently depending to the environmental conditions.

A. *Simulation of the MPPT neural controller under Standard Tests Conditions (STC)*

For the case of constant conditions, the Standard Tests Conditions (STC) are considered, S=1000W/m^2 and T= 25°C. Fig. 7 shows the results obtained for the module power, and the duty cycle D in these conditions. As it can be seen on this figure, after a short interval of time of about 5 seconds, which could be considered as a response time of the PV system, the maximum power of the module and the battery are reached and remain stable. This proves that the neural controller works well for a given constant conditions.

B. Simulation of the MPPT neural controller under variable conditions of irradiance and temperature

For this second group of tests, we have studied the influence of two important parameters in the operation of the PV system that is irradiation and temperature. We have varied each time one of these parameters while the other was kept constant. For the parameter that is varied we have also studied how the MPPT controller reacts to the rate of change of this parameter. The different scenarios developed aim to see how the MPPT neural controller operates in dynamic operating conditions.

1) Variation of solar irradiance S, T=25°C

In this case the temperature is assumed to be constant, (T= 25°C) and the solar irradiance is changed slowly and rapidly. In the following are presented the simulation results for the studied cases.

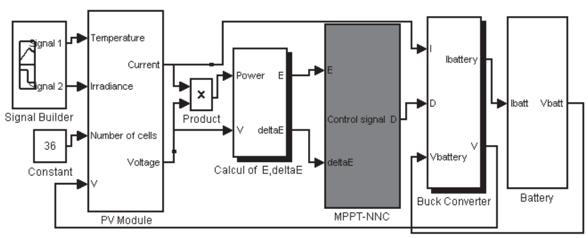

Fig. 6. Layout diagram of a PV system with a MPPT –NNC in Matlab/Simulink environment

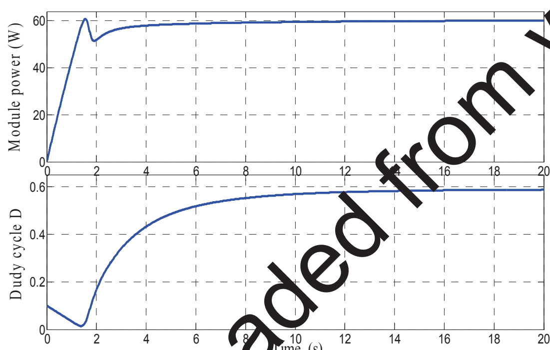

Fig. 7. Variation of the module power and the duty cycle D in STC conditions (S=1000W/m² and T= 25°C).

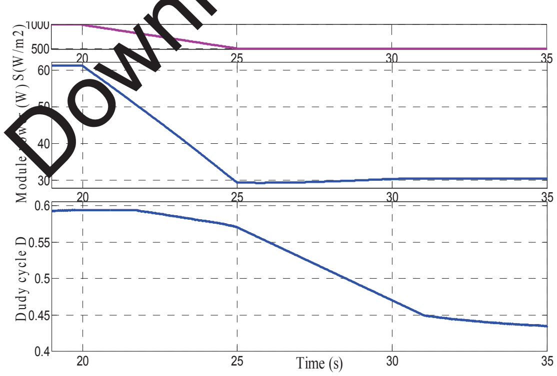

Fig. 8. Variation of the module power and the duty cycle 'D' for a fast decrease of S from 1000 to 500 W/m² in 5 seconds at T=25° C.

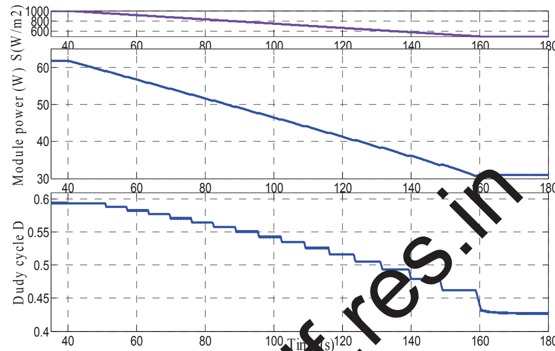

Fig. 9. Variation of the module power and the duty cycle 'D' for a slow decrease of S from 1000 to 500W/m² in 120 seconds at T= 25° C.

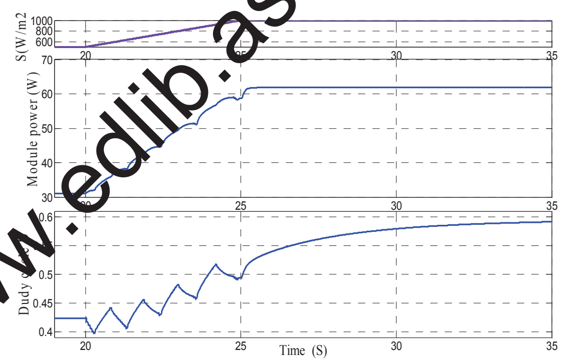

Fig.10. Variation of the module power and the duty cycle 'D' for a fast increase of S from 500 to 1000 W/m² in 5 seconds at T=25°C.

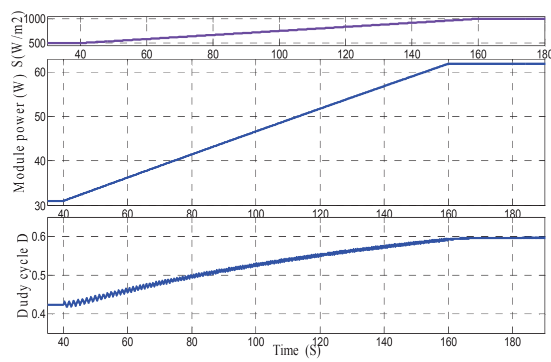

Fig. 11. Variation of the module power and the duty cycle 'D' for a slow increase of S from 500 to 1000 W/m² in 120 seconds at T= 25°C.

From Fig. 7, 8, 9 and 10, we notice that the power of the module follows the increase or the decrease of the irradiance, thus when irradiation decreases from 1000 W/m² to 500W/m² the power diminishes from 63 to 32W in 5s and 120s depending the rate of variation of the irradiance.

2) Simulation results under variable conditions of temperature

The temperature of the solar cell is an important factor that affects the solar panel characteristics and therefore the power. Similar tests as for the solar irradiance were performed and the results are presented in the following figures.

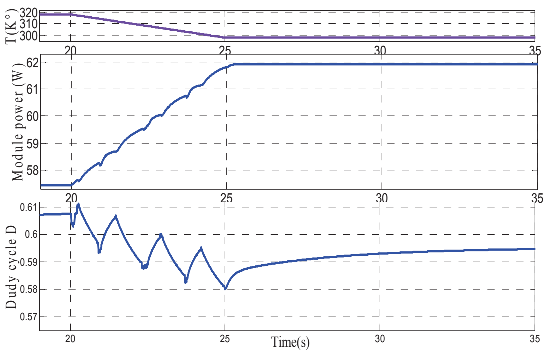

Fig. 12. Variation of the module power and the duty cycle 'D' for a fast decrease of T from 45°C to 20°C in 5 seconds at S= 1000W/m^2.

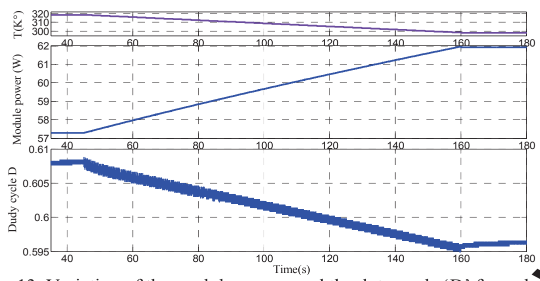

Fig. 13. Variation of the module power and the duty cycle 'D' for a slow decrease of T from 45°C to 20°C in 120 seconds at S= 1000W/m^2.

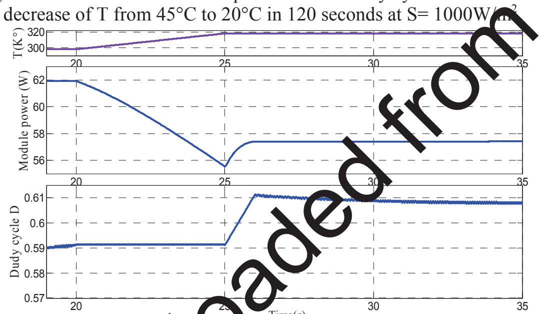

Fig.14 Variation of the module power and the duty cycle 'D' for a fast increase of T from 20°C to 45°C in 5 seconds at S=1000W/m^2.

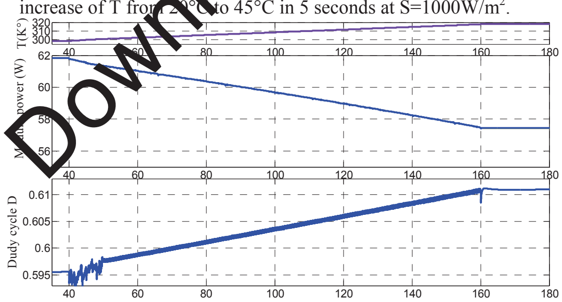

Fig.15 Variation of the module power and the duty cycle 'D' for a slow increase of T from 20°C to 45°C in 5 seconds, at S=1000W/m^2.

Inversely to irradiance, we can see on Fig. 12, 13, 14 and 15 that the maximum power of the module increases when the temperature decreases and vice versa. When the temperature increases from 25°C to 45°C the power diminishes from 63W to 57W in 5 s and 120s, at a rate of the decrease of temperature.

V. CONCLUSION

In this paper, an intelligent controller based on neural network has been designed to optimize the performance of a PV system. This controller has been tested under many conditions of solar irradiance and cell temperature. We have shown that the developed NNC algorithm achieved very good performance and fast response even in variation of climatic conditions as it requires very short time to reach and stabilize at the maximum power point hence improving the amount of energy effectively extracted from the PV modules and increasing the efficiency of the PV system.
The next step in the study concerns the behavior of the PV system with the neural controller when the solar irradiance and the cell temperature are changing at the same time. We will also investigate the influence of the variation of the load on the PV system performance. We are planning, also, to use other neural network algorithms, such as the Hopfield and Kohenen networks, to control the PV systems in order to determine the most suitable algorithm.

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Ellipsometric Study of Optical Properties of Thin Semiconductors Films

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***Abstract*—the aim of this work is to determine by ellipsometry the optical properties of semiconductor thin films made of gallium nitride, gallium arsenide and gallium phosphide.**
Ellipsometry is an optical method based on the behavior of polarized light. The light reflected on a surface induces a change in the polarization state which depends on the characteristics of the material (complex refractive index and thicknesses of the different layers constituting the device). The paper describes the experimental aspects concerning the semiconductor samples, the SE400 ellipsometer principle, and the results obtained by direct measurements of ellipsometric parameters (Psi and delta) and modeling using "*Sentech Instruments GmbH*",software.

***Index Terms*—semiconductors GaN, GaAs, GaP, ellipsometry, optical properties**

I. INTRODUCTION

The development of semiconductors materials as films has contributed to an increase of performance of electronic, photonic and photovoltaic systems including lower cost of components for mass production. The structure of the deposited films may be monolayer or multilayer with thicknesses which vary from one atomic plane (several Angstroms) to several hundreds of micrometers. Their optical properties depend on their microstructure.

The objective of this work is to determine the optical properties of thin films and semiconductor. The most optical properties are the complex refractive index and thickness, as well as all notions of transmission and reflection. For this goal ellipsometry is adapted as characterization technique of semiconductor sample set on GaAs, GaN, GaP.

Ellipsometry is an optical method based on polarized light. Indeed, the light reflection on a plane surface induces a change in the polarization state which depends on the characteristics of the material (complex refractive index and thickness of the layers).

Advanced applications of thin films have diversified in chemistry and optic fields while the optical layer applications have enabled the development radiation sensors [Bahoura, M., et al., (2008). The intentions of systems produced by films on the substrate are the access to the electrical conductivity of metalized surface for scanning electron microscope, increase or decrease the reflection (anti-reflection coating, metal mirror...), selecting of reflection or transmission in a certain range of wavelength (selective mirror, interference filters...), fabrication of protective layers. Between the conductors and insulators films, one can classify a number of solids which are semiconductors. The III-V semiconductors are compounds formed from a member of the third column and the fifth column of the periodic table. The study of their properties, and in particular the band structure shows that the lightest elements give wide band gap compounds whose properties be similar to those of insulating compounds including boron, aluminum, nitrogen, and phosphorus, are required by the semiconductor with a high carrier mobility, designed for optoelectronic or a strip structure is necessary for direct optical transitions are effective. The main materials are the III-V compounds type GaAs, GaP, GaN [Duboz, J. Y.(1999)]. The existence of the band gap explains the transparency of semiconductor infrared radiation [Duboz ,J.Y.(1999) , Han, J., at.al. (2007)].

This work shows the measurement principle of ellipsometry and the use of the SE400 ellipsometer to characterize the optical parameters of samples set by two methods: directly (measured) and indirect (modeling).

II. PRINCIPLE OF ELLIPSOMETRY

We consider a surface illuminated at an incidence i0 by a monochromatic plane wave (Fig.1). The polarization direction of the incident wave linearly polarized is identified by the angle α. The field component parallel to Oy component is called S (transverse electric relative to the plane index), and the perpendicular thereto is called P (transverse magnetic) [Azzam, R. M. A. and. Bashara N. M, (1987)].

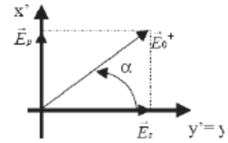

Fig. 1. Direction field in the plane perpendicular to the incident wave vector

The incident wave can be written:

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