Photovoltaic Electrical Forecasting in South Algeria

S. Hamid Oudjana, A. Hellal, and I. Hadj Mahamed

***Abstract*---**Photovoltaic electrical forecasting is significance for the optimal operation and power predication of grid-connected photovoltaic (PV) plants, and it is important task in renewable energy electrical system planning and operating. This paper explores the application of neural networks (NN) to study the design of photovoltaic electrical forecasting systems for one week ahead using weather databases include the global irradiance, and temperature of Ghardaia city (south of Algeria) for one year of 2013 using a data acquisition system in. Simulations were run and the results are discussed showing that neural networks Technique is capable to decrease the photovoltaic electrical forecasting error.

Keywords*—-Photovoltaic Electrical Forecasting, Regression, Neural Network..*

I. Introduction

THE global climate change situation is becoming more severe due to the depletion of fossil energy, so the application of renewable energy sources has been receiving more attention, the world population is growing at a rapid pace, the global energy consumed and demanded also grows. Speculation about the depletion of fossil fuel reserves is a cause of concern for most governments and economies, and together with climate change and energy security issues, drives a massive campaign for clean and renewable energy options that would supplement the current energy production technologies. The issue of reducing C02 emission amount makes the whole world concentrate on installing renewable energy resource. Therefore, the interest in the solar and wind energy is consistently increasing in these days. However, to equip energy resource holds lots of problems yet so that we cannot rely on such renewable energy amount for the national electrical system. One of the most serious problems is that energy resource is afected by weather condition a lot. Thus, the electrical produced by energy resource is provided irregularly and depletes the national electrical system stability and reliability [1,2].

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The forecasts are key to the reliable and cost effective large scale integration of photovoltaic (PV) systems into electricity grids. In addition, prediction of PV electrical is also required for the planning and resizing of large scale PV plants, balancing control, electrical system stabilization, green electrical transactions, electrical interruption warnings in autonomous electrical systems and so on [3].

The Short-term photovoltaic electrical forecasting methods are experience forecast, such as electricity elasticity coefficient, integrated electrical consumption, output and growth rate of consumption, extrapolation forecast and district load density index method. Such methods need to the value, yield and growth rate, and other data [4].

The statistical analysis methods used in the electrical forecasting are regression analysis and time series, such as linear regression model, multiple linear regressions model, nonlinear regression analysis, autoregressive (AR) model, moving average (MA) models, autoregressive moving average (ARMA) model and nonstationary time-series. The statistical analysis methods need some relationship of values and the changes among identify consumption, load, time, total output value of industry in electricity gross domestic product, and then use mathematical models to forecast. The entire process is projected to ongoing mathematical model calibration and adjustment process, which will be taken longer time to complete [5-11].

The intelligent methods based electrical forecasting are expert system, grey generation, fuzzy logic, artificial neural networks, which used in the economic environment changes, and other random factors interfere with the electrical system under load accurately forecast, which widely used to analyze numerous uncertainties and the electrical load forecast correlation. But how accurate will describe the criteria adopted for the artificial uncertainties are relatively difficult. This paper provides a neural networks models based on the temperature and irradiance data [12-15].

The objective is to develop a forecasting model which will be able to consistently forecast the energy generated by photovoltaic modules using explanatory variables available at most weather stations. The aim of this study is to enable future photovoltaic projects in Ghardaia city (south of Algeria) to be deployed at a much faster rate and at lower costs.

II. Regression Method

Regression is a statistical technique for building a link between a explanatory variables and dependent variable. The aim is to predict the dependent variable when you know the explanatory variable or establish if there is an effect of one

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variable on another.

A. Simple Linear Regression

The basic model for a deterministic set of n observations is given by equation (1):

$$Y_i = b_0 + b_1 X_i + e_i \qquad i = 1,2,...n \tag{1}$$

Y_i: dependent variable,
X_i: explanatory variable,
b_0: standard estimator,
b_1: explanatory variable estimator.

Estimators b_0 and b_1 are calculated by the least squares method.

If the electrical P_{i+1} (dependent variable) depends only on the corresponding temperature T_{i+1} (independent variable), the prediction is generated as follows:

$$P_{i+1} = b_0 + b_1 T_{i+1} + e_{i+1} \tag{2}$$

The strength of association between two variables is estimated by the correlation coefficient (r). This coefficient ranges from -1 to +1. If it is between 0.8 and 1 (absolute value), the strength of association between two variables is important. Between 0.5 and 0.8 is moderate, and between 0.2 and 0.5 it is weak:

$$r = \frac{\sum_{i=1}^{n} x_i y_i - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{\sqrt{\left[\sum_{i=1}^{n} x_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)^2\right]\left[\sum_{i=1}^{n} y_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} y_i\right)^2\right]}} \tag{3}$$

B. Multiple Linear Regression

Multiple regression is a generalization of the simple linear regression. The difference is that there are more variables to explain the dependent variable. Thus for k variables, the model become:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k \tag{4}$$

Wherein, Y is a vector of values of y while X is a matrix of independent variables x described as follows:

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} \cdots x_{1k} \\ 1 & x_{21} & x_{22} \cdots x_{2k} \\ \vdots & \vdots & \vdots \quad \vdots \\ 1 & x_{n1} & x_{n2} \cdots x_{nk} \end{bmatrix} \tag{5}$$

The estimators are calculated by the B matrix:

$$B = \begin{bmatrix} b_0 & b_1 & b_2 \cdots b_k \end{bmatrix}^T = (X^T X)^{-1} X^T Y \tag{6}$$

III. Neural Networks

From the beginning of nineties, new techniques appear to study the electrical load forecasting such as artificial neural networks. These recent techniques quickly became widely used in short-term PV forecasting. The mathematical model of an artificial neuron (Fig.1) consists essentially of an integrator that performs a weighted sum of its inputs. The result n of this sum is then transformed by a transfer function f which produces the output of a neuron. The R input neurons correspond to the vector $P = [p_1, p_2, \ldots, p_R]^T$, whereas $W = [w_{11}, w_{12}, \ldots, w_{1R}]^T$ represents the vector of the weights of the neuron. The output n of the integrator is given by the following equation:

$$n = \sum_{j=1}^{R} w_{1,j} p_j - b \tag{7}$$

To verify the performance of the forecasting model, we can calculate the mean absolute percente error:

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \frac{\left|P_t - \hat{P}_t\right|}{P_t} \tag{8}$$

P_t: Desired Electrical
$\hat{P}_t$: Forecast Electrical
n : Number of sample

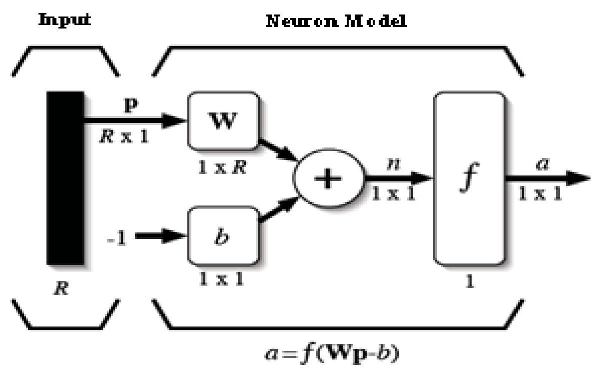

Fig. 1 Model of an artificial neuron

IV. Forecasting Models

Three models have been tested and valídate using differnet factors to virify they performances.

A. Model 1

This forecasting model requires only the temperature as an explanatory variable or as a database using simple regression and the neural network methods to predict the PV electrical for seven days ahead.

B. Model 2

The irradiance (solar radiation) factor at the previous time are used as database to predict the electrical for one week ahead, using the simple regression method and the neural network technique. Table 1 shows the correlation between the electrical and the corresponding temperature.

C. Model 3

The database of this model depends on two independent variables: the temperature and that of irradiance parametre correspondig to the same day of electrical forecasting value.

The strength of association between the generated electrical of photovoltaic module and the temperature is low

(Table I). Against by the strength of association between the current electrical and irradiance factor is very strong. The correlation coefficient ***r*** = 0.98 explains the intensity correlation, and the positive sign of this value expresses the proportional relationship of electrical with the corresponding value of irradiation, which means that when the irradiation increases the electrical generated by the PV module increases. Fig. 2 and 3 illustrate the correlation between the generated electrical of photovoltaic module and temperature, and between electrical and the irradiance factor corresponding respectively.

TABLE I.
EXPLANATORY VARIABLES CORRELATION

Explanatory Variables	**Correlation Facteur (*r*)**
Temperature	0.37
Irradiance	0.98

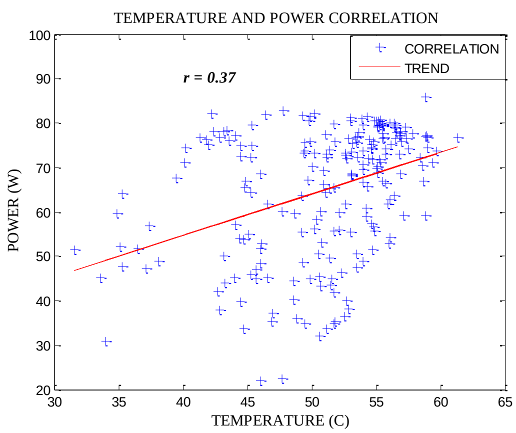

Fig. 2 Temperature vs. Electrical correlation

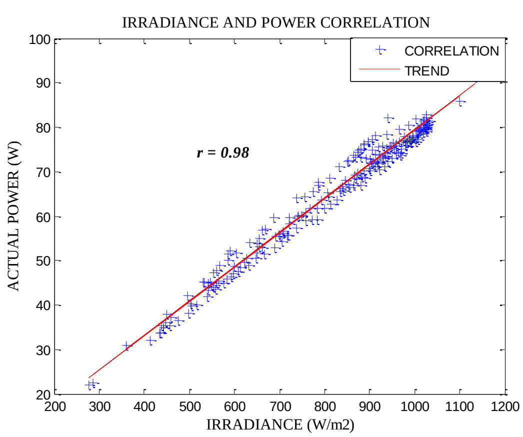

Fig. 3 Irradiance vs. Electrical Correlation

V. SIMULATIONS

To validate the three forecasting models presented, in terms of the mean relative error, we must test multiple databases. For this, we used three database of 2008: 70%, 80% and 90% of data used to train the neural network by MATLAB code that we can predict the electrical generated in one week ahead, Table II representing three databases. The three models will be tested using the method of simple regression and neural networks. The performance of each model is verified by the mean absolute percent error MAPE.

The prediction error of Model 1 (Table III) is large because only one independent variable or explanatory (temperature) was used. Its correlation with the PV module electrical is low, it is necessary to introduce other variables to improve performance. However, it is preferable to use neural networks in this case because it does not require several explanatory variables. Thus, Fig. 4 shows the electrical forecasting of this model. The difference between the desired electrical and that achieved using the regression is great because it can not predict the electrical associated with changes in temperature. On the other side, the method of neural network prediction narrowed the electrical gap to 1.48% that has a correlation with temperature by this intelligent technique.

Since the factor of radiation having a strong correlation with the electrical of the PV module, the forecast error will obviously decrease compared to model 1, and this is the case shown in Table IV, knowing that the average errors of the three tested is less than 4% using the method of simple linear regression, and the best accuracy is 1.093% using the neural network. Fig. 5 illustrates the application of Model 2 which shows the approach of the forecasting curve to that desired.

By hybridizing the model 1 and model 2, we obtain model 3, that is to say that the explanatory variables used to forecast electrical of photovoltaic module are temperature and irradiance. The accuracy of prediction using this model is even better (Table V) because the electrical produced by photovoltaic panel depends on the meteorological factors and the correlation between these variables and electrical is even stronger. Fig. 6 shows the curve prediction by multiple regression and neural networks and shows that the electrical curve are realized and that provided nearly superimposed, such that the accuracy of prediction reached 0.217% (Table V) by the NN. This means that the prediction using the parameters of temperature and irradiation is more accurate than using the variable temperature or irradiation. Table VI summarizes the difference between the regression and the neural networks.

TABLE II.
DATA SETS

Set	**Test (day)**	**Validation (day)**
01	187	188-194
02	214	215-221
03	240	241-247

TABLE III
VALIDATION OF MODEL 1 PERFORMANCE BY MAPE (%)

Set	**Simple Regression**	**Neural Networks**
01	39.148	2.717
02	21.969	1.484
03	11.754	2.082
Mean (%)	**24.290**	**2,094**

TABLE IV
VALIDATION OF MODEL 2 PERFORMANCE BY MAPE (%)

Set	**Simple Regression**	**Neural Networks**
01	4.876	6.070
02	3.250	1.093
03	1,744	3.702
Mean (%)	**3,290**	**3,621**

Table V
VALIDATION OF MODEL 3 PERFORMANCE BY MAPE (%)

Set	Multiple Regression	Neural Networks
01	0.708	0.676
02	0.767	0.758
03	0.218	0.217
Mean (%)	**0.564**	**0.550**

TABLE VI
NEURAL NETWORKS VS. REGRESSION COMPARISON

Regression	Neural Networks
requires a mathematical model	does not require a mathematical model
Several explanatory variables	Few explanatory variables
Small data base	large database
Short execution time	Long execution time

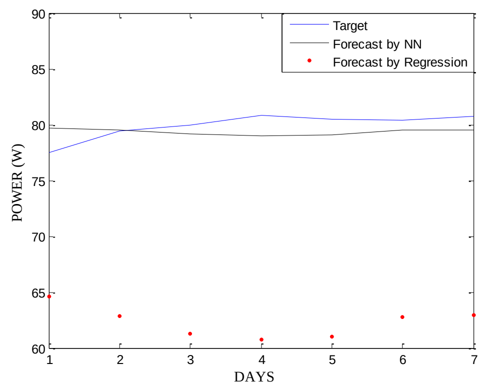

Fig. 4 PV Electrical Forecasting Using Model 1

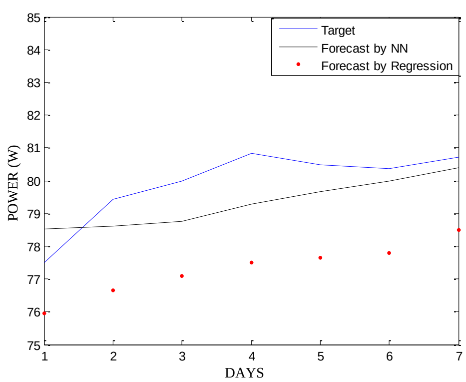

Fig. 5 PV Electrical Forecasting Using Model 2

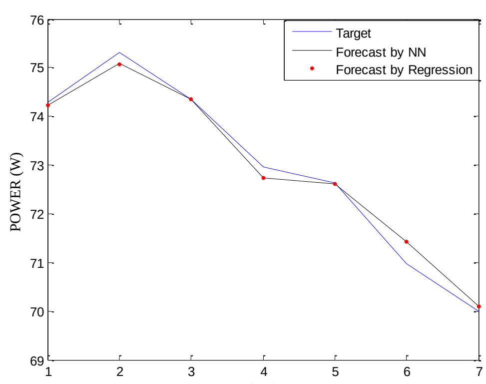

Fig. 6 PV Electrical Forecasting Using Model 3

VI. CONCLUSION

Short-term photovoltaic electrical forecasting is important to the operation of electrical system to make decisions by the dispatching center that cares to ensure electrical network security management while having a reliable and cost effective production system that meets specific environmental constraints.

The work initiated in this paper aimed to achieve a program that can predict the electrical generated by a PV generator to one week ahead at the site of Ghardaia (south of Algeria) and analyze the relationship between meteorological factors and the electrical supplied by applying the neural network technique. The regression is a standard statistical method based on a mathematical model. Against by the technique of neural networks does not require a mathematical model, but is based on artificial intelligence.

Before choosing a forecasting model of the electrical supplied by a photovoltaic module, we must first determine the correlation between independent variables and the desired electrical . For Model 1, the strength of association between temperature and electrical is low, so the forecast error is large. But the correlation between the predicted electrical and the irradiation is strong; consequently the forecast error becomes acceptable using model 2. Model 3 gave us a better accuracy, based mainly on two factors: temperature and irradiance, so that they can be used to short-term electric electrical of a photovoltaic plant. We conclude that the choice of forecast model output based on the study of the relationship of the explanatory variables with the desired electrical . Furthermore, this correlation is stronger, the model is better.

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