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One day ahead prediction of PV power production: case study of Oued-Elkebrit's station (Algeria)

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***Abstract*— The research work presented hereafter is based on real recorded database of a PV plant in production and in connection with a classical electrical grid. Datasets were processed through two types of techniques. The first one, a classical type, is based on a predictive predefined model, however, the second one is an artificial intelligent method based on neural networks. Based on the carried out experiences, we proposed a new strategy to implement the proposed techniques. The results obtained through the two methods were compared which demonstrate the superiority of the AI method in terms of precision, generalization and robustness. Obtained results for each method were recorded, analyzed and compared.**

Keywords—Renewable energy, Forecasting, PV plant, Power production, Neural network

I. Introduction

The energy on its different forms represents a vital constituent of the human life. In the course of its historical evolution, humanity has increasingly needed to consume more energy in more and more forms. The last two centuries have seen an exponential increase in the amount of energy consumed. Industrial development, consumption development, new technologies, etc. have boosted this trend to consume more and in different forms. However, the last two decades have seen an awareness of the dangers facing humanity as by continuing in this destructive policy of energy and environmental resources of the planet. All over the world, we are beginning to see the effects of this policy from the climate point of view and we began to see the limits of potential and natural resources. A new trend emerged among researchers from around the world; it consists of looking for other forms of renewable energies, sustainable and friendly to the environment. After two decades, we begin to perceive a growing hope in some of the resulting new trends and technologies of producing energy from natural renewable resources especially the sun the wind and the biomass [1]. Moreover, some of these technologies as the photovoltaic and the wind have passed the experimental stage towards the practical production stage [2], [3], [4]. Global word-wide production of these two types of new resources began to take place as possible replacement solutions especially in rural and poor areas [5].

However, such new technologies still encounter many challenges that have to be overcome. These challenges are of different types beginning by economical ones, technical ones and even social challenges [6]. Technical problems received particular interests by researchers since improvements in such profile permit improvements for all encountered problems and facilitate insertion of such technologies in the industries and even in the day-life of the society.

Among renewable energy solutions, photovoltaic systems became one of the most successful and promising technologies of the new trends. PV electricity production benefits from the large deployment of the principal resource, namely the sun and its relative availability in almost regions of the world. PV systems have been set up to function as completely independent systems and thus provide electricity to individual communities [7] or as systems integrated into conventional power grids [8]. Each one of these configurations rises its own problems and challenges. However, a well known challenge that is common for each of them is the problem of intermittence. Indeed, it's a real and practical problem that is related to the nature of the resource (the sun) and its interaction with some other geometric (day vs night) and climatic (clouds, temperature, wind speed, humidity and pressure) characteristics of our planet [9] [10]. This major problem was largely studied by researchers and two principal strategies were proposed to limit its effects on the designed PV production plants. The first strategy is based on the development of storage components and structures for the produced electrical energy and the second one is based on the prediction of the PV plant's electrical production. Our proposed research work presented hereafter will deal with the intermittence problem according to the second strategy by studying and comparing two techniques applied to a real database recorded on a real PV plan already in production and in connection with a classical electrical grid.

In the following of this research paper we will firstly give an overview of the principal methods and techniques used as forecasting solution to the intermittence problem on the PV plants then we will introduce, in section 3, the two methods that

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will be investigated according to the PV plant's database. In section 4, we will give a detailed statistical analysis of the datasets of the working database. Section 5 will contain the obtained results and their discussions. We will finally give the conclusions and the perspectives in section 6.

II. FORECASTING TECHNIQUES AND METHODS OVERVIEW

Due to the fact that the solar radiation represents an enormous amount of free, economic, largely deployed, simply accessible and friendly environment mine of energy, it received a special attention by researchers, economists and even politicians around the world. This attention participates in its fast development and deployment which permits a real growth in worldwide PV production. Indeed, according to the IEA (International Energy Agency) in an interval of ten years, the world produced electricity by PV plants passed from the reduced number of 11.9 TWh in 2008 to the phenomenal amount of 570 TWh in 2018. The SDS (Sustainable Development Scenario) forecasts an annually 16% growth of electricity PV production which will led it to about 3300 TWh by 2030.

However, production development depends essentially on technical improvements of the principal related parameters and the capacity of realized researches to overcome the principal encountered challenges. As one of the inevitable and unavoidable problem in PV electricity production, the intermittence phenomenon of the solar radiation received a particular attention by community of the researchers of the domain. As mentioned in the introduction of this paper, two solutions were adopted to deal this problem. The first one is the development of storage means and the second one is the prediction or as commonly called forecasting strategy.

Forecasting techniques and methods can be classified according to three criterions. The first one is the temporal extent of the prediction process. According to this criterion, forecasting can be performed in short-term covering the period from one second to 24 hours ahead [13], [14], [15], medium-term from 24 hours and up to one month [16], [17] and long-term forecasting for periods up one or more years [18], [19]. According to the second criterion which is parameters used as inputs of the prediction system, forecasting techniques can be classified in two principal classes; techniques based on climatic parameters [20] [21] [22] and those based satellite images and weather forecasting techniques [23] [24]. The last criterion which was considered for this type of classification is the processing technique. Here also, two principal classed could be considered; techniques based on classical processing methods such as ARMA, ARIMA and ARX [25][26] and those based on the so called intelligent processing methods like ANN, fuzzy, bee colony, Genetic algorithms etc [27][28][29].

However, this classification still partially incomplete since combined techniques are also used in many research papers. Combinations are intra-criterion and inter-criterion.

III. GLOBAL STATISTICS ON DATASETS OF THE DATABASE

The database contains measures of the global power produced by the PV plant and the five related climatic parameters, namely the solar radiation, the temperature, the humidity, the atmospheric pressure and the wind speed.

Here after we expose some of the basic statistics of the recorded database.

- Figure 1 shows that the monthly average of the total irradiation in 2017 varies from 183.08 W / m² during the month of January to 528.88 W / m² during the month of July, and from 219.99 W / m² during the month of January to 525.64 W / m² during the month of July for the year 2018. The annual average of the global radiation during 2017 is 359.23W/m² and 356.82W/m² for 2018.

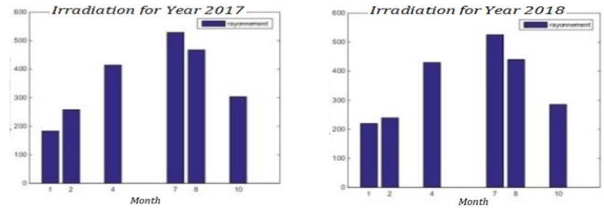

Figure 1 Monthly irradiation average of the PV plant during 2017 and 2018

- The maximum value of the monthly average temperatures appears in July (31.85°C) for 2017 and also in the same month July (33.14°C) for 2018, while the minimum value is recorded in January (7.16°C) for 2017 and in February (9.22°C) for 2018. The average annual temperature during 2017 is 20.06°C and for 2018 19.73°C. (Figure 2).

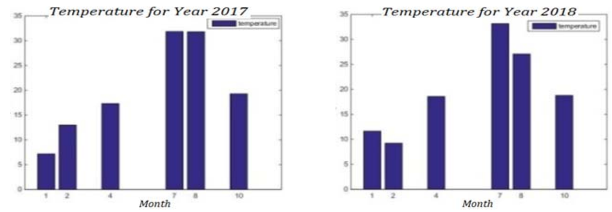

Figure 2 Monthly temperature average of the PV plant during 2017 and 2018

- The lowest monthly average of the relative humidity (during the summer) exceeds 28% for 2017 and 26% for 2018 (Figure 3), while the highest monthly average (during the Winter) is 55% for 2017 and 58% for 2018. Annual average during 2017 is 42.92%, and 47.30% in 2018.

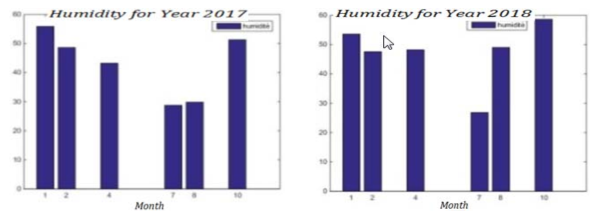

Figure 3 Monthly humidity average of the PV plant during 2017 and 2018

- The maximum value of the monthly wind speed averages appears in January (4.97 m/s) for 2017 and in February (4.72 m/s) for 2018, while the minimum value was recorded in October (2.99 m/s) for 2017 and in August (3.09 m/s) for 2018. The annual average wind speed in 2017 is 3.77 m/s and 4.01 m / s in 2018.

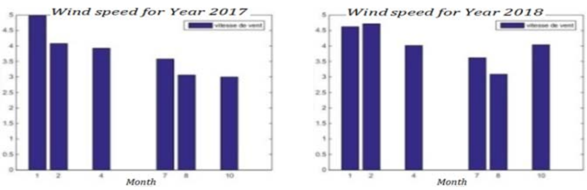

Figure 4 Monthly wind speed average of the PV plant during 2017 and 2018

- The maximum value of the pressure appears in October 938.98 hPa for 2017 and 937.84 hPa in January for 2018, while the minimum value was recorded in April 934.25 hPa for 2017 and 928.19 hPa in February for 2018. Its annual average during the year 2017 is 936.07 hPa and 933.75 hPa during 2018.

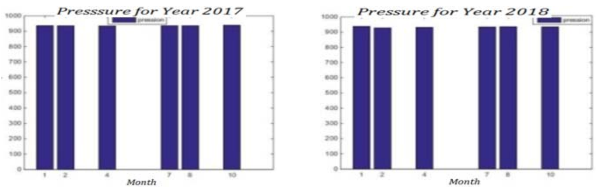

Figure 5 Monthly pressure average of the PV plant during 2017 and 2018

To have a comparative idea (on the shape of the measured parameters), we give on the same plot (figure 6) a normalized presentation of the power production with the five climatic related parameters.

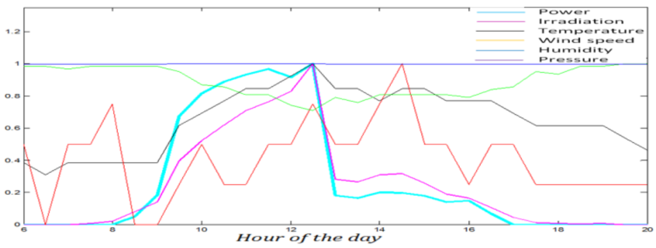

Figure 6 Example of normalized recorded power and climatic parameters for a day of January 2017

The curves in Figure 6 are normalized to allow a comparison of form and not of values. They show very well the close relationship between power and radiation compared to other parameters. However, one can easily notice that when there is a de-correlation between these two main quantities, it is mainly under the influence of these other secondary parameters. We have noticed that these secondary parameters intervene only from certain extreme values. The most obvious example is the temperature whose influence is felt only at values above 43 ° C. For the pressure for example, its values are very close to each other which makes their representation in the previous figure almost constant which does not allow seeing its real influence.

A. Relationship between produced power and climatic parameters

To decompose a little more the different relations that link the power produced to the different parameters, we had recourse to the function of inter-correlation whose use in signal processing always allows measuring the relationship of dependence between two or more signals.

The following figures (figure 7 to figure ???) represents the inter-correlation between the produced power and respectively the radiation, the temperature, the wind speed, the humidity and the pressure. On each figure the inter-correlation is given for the six months of our database.

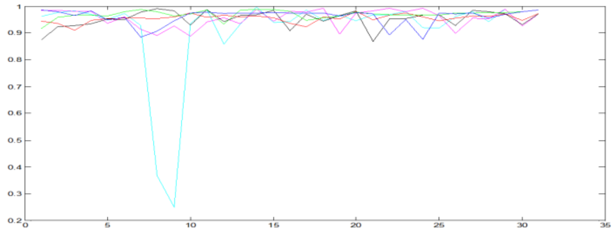

Figure 7 Inter-correlation between the produced power and the radiation for the six months of the database (year 2017)

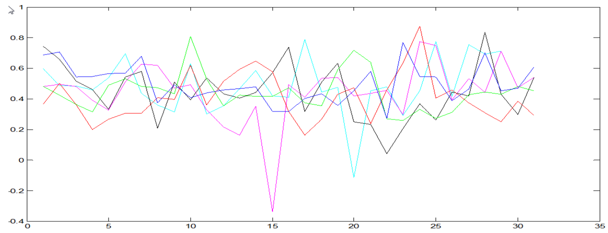

Figure 8 Inter-correlation between the produced power and the temperature for the six months of the database (year 2017)

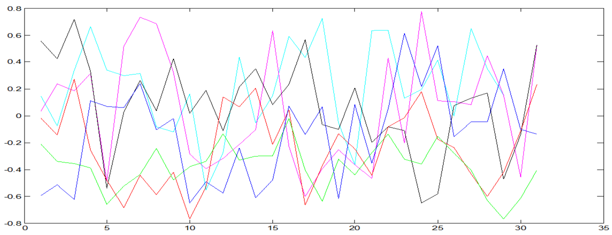

Figure 9 Inter-correlation between the produced power and the wind speed for the six months of the database (year 2017)

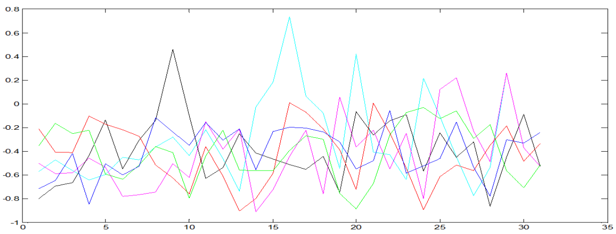

Figure 10 Inter-correlation between the produced power and the humidity for the six months of the database (year 2017)

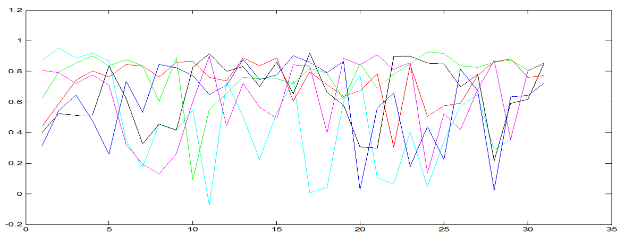

Figure 11 Inter-correlation between the produced power and the pressure for the six months of the database (year 2017)

Based on the precedent figures, we make following remarks:

figure 7: We can easily notice the very high dependence (inter-correlation ≈ 1) between the power and the radiation as well as the daily regularity, over the whole month and even over the year.

Figure 8 and figure 11: The dependence is lower between the power on the one hand and the temperature (average inter-correlation ≈ 0.53) and the pressure (average inter-correlation ≈ 0.66) on the other hand. However, we can notice an average regularity between the different months studied.

Figure 9 and figure 10: The daily and monthly overall dependence is very low for the Wind speed parameter (mean inter-correlation ≈ 0.11) and the Humidity parameter (mean inter-correlation ≈ -0.31) accompanied by a remarkable irregularity daily and monthly.

These remarks will be taken into account in the implementation of the forecasting solutions that will be studied in the following.

Based on what has been presented in section 2 as a bibliographic study of some methods using the prediction technique to solve the problem of intermittency on the one hand and using the remarks selected from the study previously carried out in this section on the other hand, we have chosen to test and compare the results of two methods, one representative of the prediction model based on a predictive model and the other one belonging to the family of artificial intelligence methods based on the neural networks.

The comparison was made with reference to a well known and largely used error measure, namely the Mean Absolute Percentage Error (MAPE). Several authors adopted this type of error measure to indicate the quality of their proposed forecasting method or system. We adopted it firstly to measure the accuracy of our proposed method and secondly to have the possibility to compare its accuracy with those obtained through the other techniques and systems.

The MAPE is mathematically expressed as given in Equation 1

$$MAPE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| \frac{PrP_i - P_i}{P_i} \right| \quad (1)$$

Where N is the number of processed values, PrP_i the predicted (forecasted) power's value and P_i is the really produced power value.

IV. Experiences, Results and Discussion

The PV plant is implanted on an estimated area of 30 h and located in the region of Souk-Ahras (Algeria) between 35.93 ° of altitude and 7.91 ° of longitude with an altitude of 614 m. it has a Mediterranean climate characterized by hot, dry summers (May to August) and mild, wet winters (November to March). The Photovoltaic plant is composed of 48,048 Polycrystalline Silicon photovoltaic modules with 250Wp each. Each sub-field consists of 4,004 photovoltaic modules with an installed capacity of 1,001 MWp. Each subfield is equipped with two centralized inverters and a step-up transformer. These inverters, with a 315V output voltage, are connected on the low voltage side via AC cables to the 1250kVA step-up transformer which raises the voltage to 31.5Kv. This plant was commissioned on 23/04/2014 and has a theoretical capacity of 15 megawatts.

Figure 12 Global view of a part of the PV plant of Oued-Kebrit (Algeria)

We used recordings done every 30 minutes for six months (two winter months January and February, one spring month April, two summer months July and August and one fall month October) of the years 2017 and 2018. After the deletion of the data of the night, nearly 62640 data records were used to form the experiencing database.

A. Method based on a predictive model

For this method we propose an empirical model that exploits the similarity between the daily distributions of power under influences of the different parameters.

The overall model used is as follows:

$$PrP(i) = \sum_{i=1}^{M} \sum_{p=1}^{N} f(p) * pr(p) * P(i-p) \quad (2)$$

Where :

PrP (i) is the predicted power at the instant i

f (p) is the weighting factor that represents the weight of the contribution of the power value P(p) as a function of the influence parameter (Radiation, Temperature, Wind Speed, Humidity and Pressure). In our case we set this parameter to the following respective values: 0.6, 0.15, 0.05, 0.00 and 0.20 and this in agreement with the previous remarks and following the different tests carried out on the model in question.

pr (p) is the measurement parameter of the influence of the power P(p) on the value of the power to be predicted PrP (i).

We have tested this model according to two versions:

a) Predictive model based on data from the same day:

In this case we tested the model using only the data of the same day. Thus, the prediction is delayed a certain time (to be chosen) until the accumulation of a minimum of information on the power produced at the beginning of the day in question as well as on the different parameters of influence.

In this case, P(p) will represent the powers recorded in the early hours of the day and N the prediction delay allowed. M will represent the number of measurement points of the powers to predict. pr (p) will represent the correlation factor between the power produced and the influence factor in question.

The curves of the following figures give an overview of the results obtained and this, by testing the model according to several cases of the time delay N and for different configuration of pr (p)

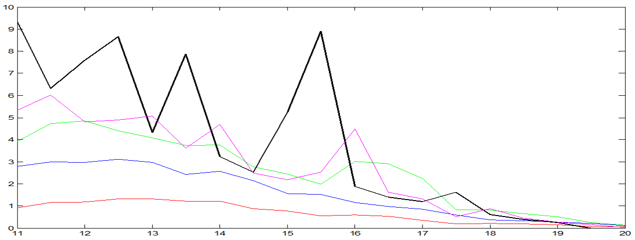

Figure13 Real power (Black) compared to predicted ones (colored) for different choices of pr(p) for a randomly chosen day of January (year 2017). N=10

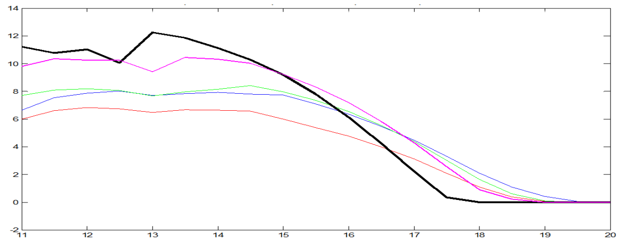

Figure 14 Real power (Black) compared to predicted ones (colored) for different choices of pr(p) for a randomly chosen day of July (year 2017). N=10

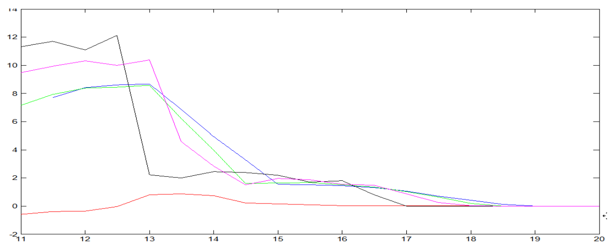

Figure15 Real power (Black) compared to predicted ones (colored) for different choices of pr(p) for a randomly chosen day of October (year 2017). N=10

The three sets of previous curves are an example of the application of the chosen prediction model for three different randomly selected days from the months of February, July and October. The colored curves are those representing the values of the predicted powers for different choices of the parameters pr(p) and f(p). The delay factor N is here equal to 10 which represents a prediction delay of 5 hours with respect to the sampling start time of the measurements.

The quality of predicted power still insufficient compared to the real power since for the best case (here figure 14), an error of 19.7% is measured. We compile the average error for the predicted power on the six months under study here and it was about 27% with the best results (about 11%) obtained for some days of July and the worst cases were recorded for some days of January 2017 and February 2018 (respectively about 41% and 43%).

The following two figures are for the same case but for N equal only 5, which represents a prediction delay of 2.5 hours.

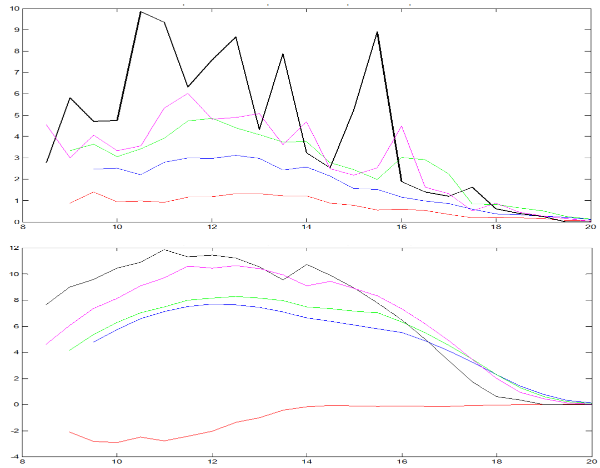

Figure 16 Real power (Black) compared to predicted ones (colored) for different choices of pr(p) for two days of January and August (year 2017). N=5

Despite the relatively small delay (N = 5) compared to that of the previous curves (N = 10), we notice comparable results. However, in both cases the prediction model lacks robustness since it does not allow precise monitoring when the frequency of variation of the power values increases sharply, which is very apparent on the first set of curves of figure 16.

b) Predictive model based on data from previous days:

In this case, we used the same model but instead of relying on the data of the same day, we used the P(i-p) as the average of the previous days

This average is weighted by the inter-correlation between the different influence parameters of the days supported and those of the day in question.

The mathematical formulation of this expression is as follows:

$$P(i-p) = \sum_{i=1}^{k}\sum_{j=1}^{5} InC(j) * P(i) \qquad (3)$$

Where P(i) is the power of the day taken into consideration and InC(j) the inter-correlation between the parameter j (radiation, temperature, ...) of this day and that of the day to be predicted.

We give on the following figures the results of the application of this variant using the previous two days then using the previous 5 days with a prediction delay of N = 5 and two different days one from January and the other from August.

The two sets of curves demonstrate an important enhancement on the quality of prediction using the two previous days, compared to those using only the recorded data of the same day. The compiled error for the six months is about 13%.

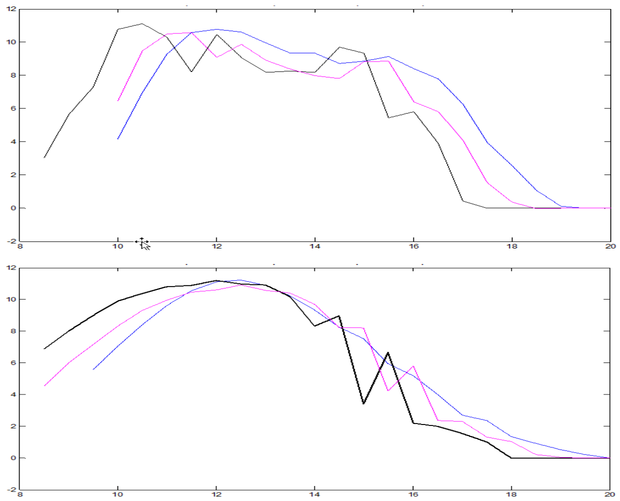

Figure 17 Real power (Black) compared to predicted ones (colored) for 2 choices of pr(p) for a randomly chosen 2 days of January and August N=5, k=2

Like it appears in the two examples of curve sets of the following figure 18, we made the remark that using the 5 previous days didn't give any significant enhancement compared to the case when we used only the 2 previous days. This will be due to the fact that similarity of climatic parameters of the previous days is more important than the number of days that will be used for prediction process.

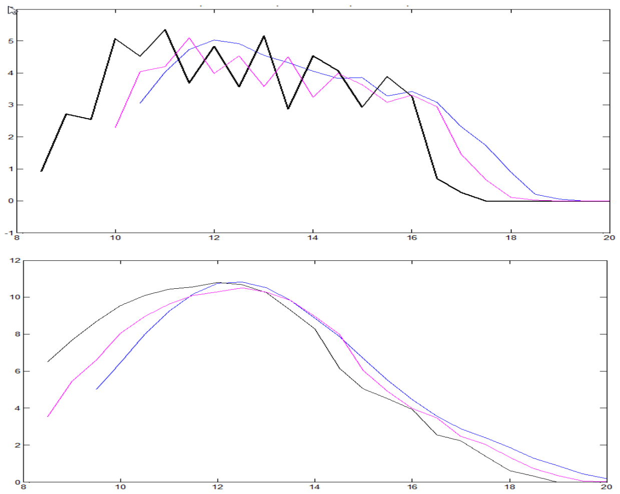

Figure 18 Real power (Black) compared to predicted ones (colored) for 2 choices of pr(p) for a randomly chosen 2 days of January and August N=5, k=5

B. Neural network predictor

As presented in the previous section, neural networks have been the subject of intense and profound exploration for the resolution of all types of problems encountered in science and technology. They are considered one of the most effective and flexible intelligent methods. Not based on predefined models but rather on a learning programmable structure whose ability to copy the behavior of any system is phenomenal. A neural network needs only examples of Input-Output couples that represent the behavior of the system whose behavior is to be copied. However, the neural network needs a huge amount of examples that are diversified and representative so that it becomes, after the learning phase, a general and robust copy of the original system.

In our case we have had recourse to the test of this type of so-called intelligent solution to allow the prediction of the behavior of the solar cells producing the electric energy under the direct influence of the different climatic parameters. Thus, we chose to test one of the simplest type of neural network namely the back propagation neuron network.

The inputs of the network being of course the climatic parameters already exposed previously. The outputs are none other than the recorded powers. However, the output vectors have been shifted (late) from those of the inputs in order to teach the network the prediction behavior we are looking for. The shift rate was subject to the different tests that were performed. Influence parameters were also subject to testing by gradually combining them into the input vectors of the network.

We therefore chose, for our work, to use a neural classifier of the 'multilayer' type with back propagation. The NN is formed of three layers of neurons; a hidden layer and the two standard input and output layers. The structure used is the following:

The number of neurons at the input is a function of the number of parameters of the attribute vectors that controls the fineness of representation of the climatic parameters by the characterization vector and influences the structure of the neural network. The number of neurons in the output layer is a function of the number of power points (number of classes) that the network will predict. In the case of our experimental base we chose to make a short-term prediction and thus a few hours of the same day. We therefore planned 14 outings representing an extended of 7 hours of the day from 10:00 to 18:00.

After several tests on different network drive functions we have chosen to retain the 'Resilient propagation' function which allows to obtain the best results. Moreover, even in the literature, it is the most used in real classification problems. For the activation functions at the three layers we retained the combination: Linear ---- Sigmoid-logarithmic --- saturation-linear.

The learning base has been divided into 2 parts. The first part contains the 18-day data from each of the 6 months of testing. The second contains the data for the rest of the days of each month.

In what follows we will present the results obtained for different types of entries.

a) Input Vectors: Recorded power values.

In this case we have chosen to train the NN to predict the values of future powers by having only information on the power values already recorded for the hours elapsed. The input layer of the network will have only 8 neurons corresponding to the 8 half-hours of the time interval 6: 00-9: 30.

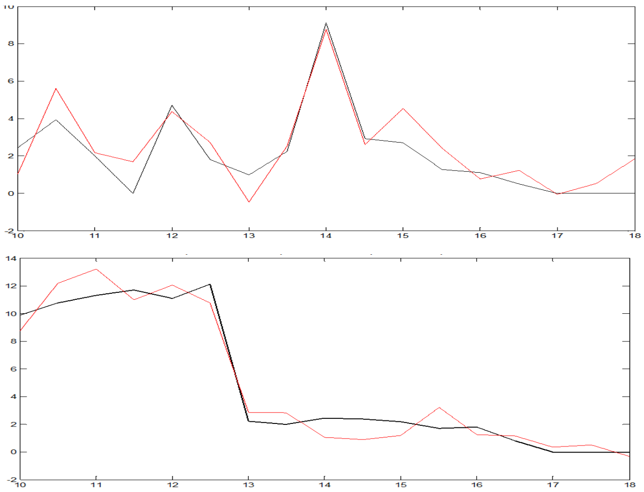

Figure 20 Curves of the predicted power (red) compared to the real power (black) for 2 days of 2 different months (January and July). NN input formed by previuos power recorded values

b) Input Vectors: Recorded power values and radiation values.

In this case we have chosen to train the network to predict future power values by having information on the power values already recorded for the elapsed hours as well as the values of the radiation parameter. In this case, the input layer of the network will contain 16 neurons corresponding to the 8 recorded power values for the time interval 6: 00-9: 30 and the 8 recorded values of the radiation.

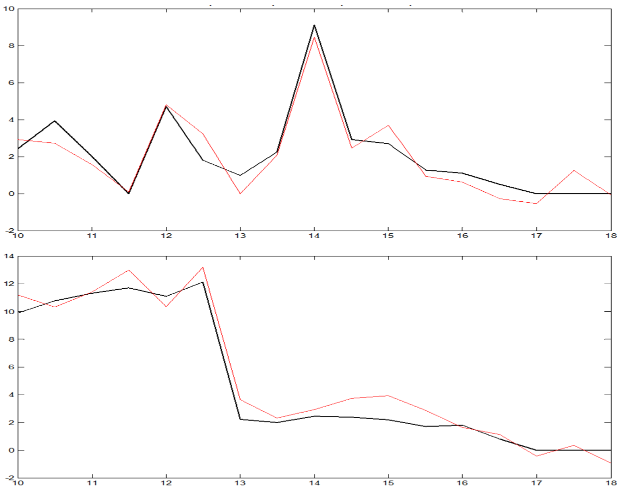

Figure 21 Curves of the predicted power (red) compared to the real power (black) for 2 days of 2 different months (January and July). NN input formed by previuos power and radiation recorded values

c) Input Vectors: Recorded power values, radiation values and temperature values.

In this case we have chosen to train the network to predict the values of future powers by having information on the already recorded previous power values for the elapsed hours as well as the values of the radiation parameter and that of the temperature parameter. In this case, the input layer of the network will contain 24 neurons corresponding to the 8 power values for the time interval 6:00 to 9:30, the 8 values of the radiation as well as the 8 values of the temperature.

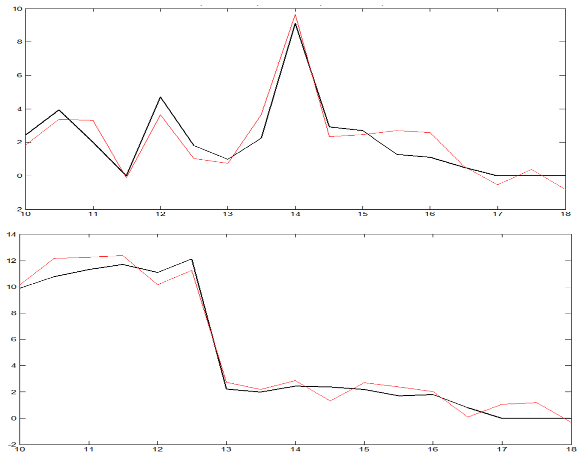

Figure 22 Curves of the predicted power (red) compared to the real power (black) for 2 days of 2 different months (January and July). NN input formed by previous power, radiation and temperature recorded values

d) Input Vectors: Recorded power values, radiation values and pressure values.

In this case, we trained the NN using the previous recorded values of the power, the radiation and the pressure. The NN therefore remains with the same configuration.

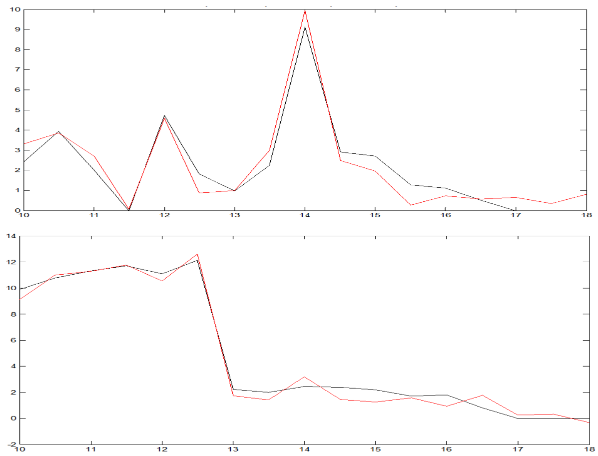

Figure 23 Curves of the predicted power (red) compared to the real power (black) for 2 days of 2 different months (January and July). NN input formed by previous power, radiation and pressure recorded values

TABLE I. COMPARAISON BETWEEN TECHNIQUES AND METHODS IN TERMS OF MSE AND STD

Technique	**Method**	**MAPE %**	**STD**
Predictive model	Recorded power values of the same day	27	7,2
	Recorded power values of the 2 previous day	13	3.6
	Recorded power values of the 5 previous day	14	6.3
Neural Network	Elapsed power values as inputs of the NN	11	4
	Elapsed power and radiation values as inputs of the NN	8	3.5
	Elapsed power, radiation and temperature values as inputs of the NN	9	4
	Elapsed power, radiation and pressure values as inputs of the NN	7	3.2

In the table below we give the global values of the mean squared error and those of the standard deviation calculated over all the test days for the different methods presented previously.

V. Conclusion

This research work was dedicated to a case study of an existing productive PV plant related to a classical electrical network. The PV power forecasting was our principal studied issue. Thus, we collected datasets from the plant, studied the statistics of our data and proposed to deal with the treated problem according to two principal techniques. A classical technique based on an adaptive time-series model and a so called intelligent method based on a neural network. For each technique, results were recorded, discussed and compared.

As perspectives of this research work, an extended study has to be done on a larger database which will allow proposing an integrated intelligent control that exploits the forecasting results to enhance the adaptation process between the power plant and the existing electrical net.

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