Multi-horizon Irradiation Forecasting Using Time Series Models

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Abstract

As fossil fuels combustion poses a real public health problem, PV and wind energy sources seem good alternatives. The main advantage is the renewable and inexhaustible aspects and the main disadvantages are related to their intermittencies. This paper deals with a solution to solve this problem: the forecasting of the renewable energy sources and more precisely the forecasting of solar irradiation. Several methods have been developed by experts and can be divided in two main groups: (i) methods using mathematical formalism of Times Series (TS) and (ii) Numerical Weather Prediction (NWP) models. Depending on the horizon of prediction or by the spatial resolution to be considered some of these methods are more effective compared to others. In this work we focus on the grid manager's point of view interested by four horizons: d+1; h+24, h+1 and m+5. Thus we tested different time series forecasting models for Mediterranean locations in order to prioritize different predictors. For the d+1 horizon, we conclude to use an approach based on neural network being careful to make stationary the time series, and to use exogenous variables. For the h+1 horizon, a hybrid methodology combining the robustness of the autoregressive models and the non-linearity of the connectionist models provides satisfactory results. For the h+24 case, neural networks with multiple outputs give very good results. For m+5 horizon, even if neural networks are the most effective, the simplicity and the relatively good results shown by the persistence-based approach, lead us to recommend it. All the proposed methodologies and results are complementary to the prediction studies available in the literature. We can also conclude that the methodologies developed could be included as prediction tools in the global command control systems of energy sources.

Keywords: Time series; artificial neural networks; stationarity; autoregressive moving average; prediction; global radiation;

1. Introduction

To overcome the intermittency problem related to renewable energy sources three solutions can be envisaged: split and better distribute the total available power, predict the resource to manage the

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transition between different energies sources or store the energy excess to redistribute it at the right time [5,6]. This paper deals with the second solution: the forecasting of the renewable energy sources. Several methods have been developed and can be divided in two main groups: (i) methods using mathematical formalism of Times Series (TS), (ii) numerical weather prediction (NWP) model and weather satellite imagery. According to the horizon some of these methods are more effective compared to others [8]. Considering the grid manager's point of view, needs in terms of prediction of intermittent energy like the solar resource can be distinguished according to the considered horizon: the resource that will be available on the following days (d+1, d+2 et d+3), the next day by hourly step (h+24), during the next hour (h+1), and in the five next minutes (m+5).. In this paper we propose, horizon by horizon, a classification of predictor tested on various Mediterranean towns. Our goal is to provide robust predictors and the most generic approach.

In the next, the time series forecasting models proposed in the literature are first reviewed. In section 3 we will detail the methodologies of prediction we have tested, taking care to explain the TS formalism dedicated to the global solar radiation modeling and the need to make it stationary. Then we will expose the result of comparison between modeling and measure in the daily case, hourly case and five minutes case. Finally we will close the paper with a conclusion and a comparison of the results with those from the literature, emphasizing the link between predictor performance and type of horizon.

2. Short Review

Optimal use of renewable energy requires a good characterization and good predictive potential for size detectors or estimate the potential energy power plants [9,10]. There are a lot of models allowing TS predictions. It is possible to list them into four groups [11,12]:

naïve models are essential to verify the relevance of complex models. Include persistence, average or the k-nearest neighbors (k-NN) [13-16];

- conditional probability models are rarely mentioned in the literature regarding global radiation. Include Markov chains and predictions based on Bayesian inference [17-22];
- reference models based on the family of autoregressive moving average, ARMA [23,24];
- connectionist models (artificial neural network) and more particularly the Multi-Layer Perceptron (MLP) which is the artificial neural networks architecture the most often used [25-27].

3. The following deals with the two last groups: ARMA and neural network models. Indeed ARMA is the most classical and popular for time series modeling and artificial neural network seems to be the best alternative to conventional approaches. As climate of the earth is dominated by non-linear processes, ANN by its non-linear nature is effective to predict cloudy days and so solar radiation. Concerning the prediction of solar radiation, we can cite works of Mellit [26,27] in which it is possible to find a synthesis of the coupling of MLP with global radiation. According to the literature, the parameters that influence the prediction are manifold, so it is difficult to use the results from other studies. Considering this fact, it may be interesting to test methods or parameters even though they have not necessarily been proven in other studies. Based on the foregoing, all parameters inherent to the MLP or ARMA method must be studied for each tested site. Methodology

The methodology used in this work is based on time series forecasting. A Time Series (TS) is intuitively defined as an ordered sequence of past values of the variable that we are trying to predict [24]. Thus, the current value at t of the TS x is noted x_t where t, the time index, is between 1 and n, with n is the total number of observations. We call h the number of values to predict. The prediction of time series from (n+1) to (n+h), knowing the historic from x_1 to x_n, is called the prediction horizon (horizon 1,…, horizon h). For the horizon 1, the general formalism of the prediction will be represented by Equation 1 where ϵ represents the error between the prediction and the measurement, f_n the model to estimate and t time index taking the (n-p) following values: n, n-1,…, p+1, p. Where n is the number of observations and p the number of model parameters (it is assumed that $n \gg p$) [44,45].

$$x_{(t+1)}=f_n\,(x_t,x_{(t-1)},\ldots,x_{(t-p+1)})+\epsilon(t+1) \qquad (1)$$

To estimate the f_n model, a stationarity hypothesis is often necessary. This result originally shown for ARMA methods [23,24] can be also applicable for the study and prediction with neural network [46,47]. We can also note that few authors suggest that periodic nature of a time series can also be captured from the AI models like MLP, very often with the inclusion of a time indicator [36]. However we have considered that in practice, the input data must be stationary to use an MLP. In previous works [44,45], we have developed sophisticated methods to make the global radiation time series stationary. We have demonstrated that the use of the clear sky index (CSI) obtained with Solis model [48] is the more reliable in Mediterranean places. As the seasonality is often not completely erased after this operation, we use a method of seasonal adjustments (seasonal variance corrected by periodic coefficients) based on the moving average [24] (CSI*). The chosen method is essentially interesting for the case of a deterministic nature of the series seasonality (true for the global radiation series) but not for the stochastic seasonality [23]. It is also possible to use a variant of CSI, considering only the radiation outside the atmosphere, we obtain in this way the clearness index (k) [49] and k* with the previous method of seasonal corrections.

We decided to establish a homogeneous experimental protocol for each considered horizon. Thereby, for all horizons studied (d+1, h+1, h+24 and m+5), we have compared ARMA and MLP predictors against at least one naive predictor (e.g. persistence). We focused our work on a general methodology for estimating the prediction error:

- test of prediction over a long period, not on "well chosen" days;
- use of RMSE to penalize large deviations [50];
- normalization of RMSE for comparisons on many sites:

$$nRMSE=\left(\frac{\left\langle\left(\hat{X}-X\right)^2\right\rangle}{\left\langle X^2\right\rangle}\right)^{\frac{1}{2}} \qquad (2)$$

- no cumulative predictions except for specific studies which has the effect of average the error and decrease it;
- distribution of errors according to seasons because the energy consumption is not the same throughout the year;
- tests on several locations, in order to avoid phenomena regional climates;
- use of a naive predictor as a reference for prediction to evaluate the proposed methodology (balance between model complexity and quality of prediction);
- use of confidence interval to define margin of error, as e.g. the classical IC95%, in order to provide information on the prediction robustness.

For ARMA and MLP methods, we have studied the impact of stationary process for the indexes CSI, k and relative seasonal adjustments (CSI* and k*). Concerning MLP, we studied the contribution of exogenous meteorological data (multivariate method) at different time lags and data issued from a numerical weather prediction model (NWP). The confidence interval has been calculated after at least six training simulations. We also studied the performance of a hybrid ARMA/ANN model from a rule based on the analysis of hourly data series. Finally we evaluated for each method the error estimation for annual and seasonal periods: Winter, Spring, Summer and Autumn. It should be noted that due to the difficulty to obtain data, the protocol could not be followed homogeneously for all data. The following section presents the results and for each horizon in chronological order.

4. Results

Data used in the experiments are related to the French meteorological organization database. Our goal is to provide robust and predictive methodology as generic as possible, avoiding falling into the specifics of a place. The non-homogeneity strict of manipulations is due to this typical construction. In fact it is very difficult to obtain quality data. At the beginning there was not much data available and after first experiments it seemed to be interesting to test our method on a larger sample. The table below lists for each horizon all manipulations performed and the data associated.

Table 2: list of manipulations performed and data associated with each horizon.

Horizon	Predictor used	Stationary method	Variable selection	Data associated
d+1	Mean, persistence, *SARIMA*, Bayesian inference, Markov chains, k-NN, *ANN*	*CSI*, k, *CSI**, k*	*PACF*, cross correlation	Ajaccio (1971:1989) and Bastia/Ajaccio (1998:2007)
h+1	Mean, persistence, ARIMA, ANN	CSI, k	PACF, cross correlation, linear regression	Ajaccio/ Bastia/ Marseille/ Montpellier/ Nice (1998:2007)
h+24	Persistence, ARMA, ANN	CSI, k	PACF, cross correlation	Ajaccio (1999:2008)
m+5	Persistence, ARMA, ANN	CSI, k	PACF, cross correlation	Ajaccio (2009,2010)

For the most complete horizon (hourly case), the data used to test models are from 5 coastal cities located in the Mediterranean area and near mountains: Montpellier (43°4'N / 3°5'E, 2 m alt), Nice (43°4'N / 7°1'E, 2 m alt), Marseille (43°2'N / 5°2'E, 5 m alt), Bastia (42°3'N / 9°3'E , 10 m alt) and Ajaccio (41°5'N / 8°5'E, 4 m alt). The available data are global radiation, pressure (P, Pa; average and daily gradient , measured by numerical barometer during 1 hour), nebulosity (N, Octas), ambient temperature (T, °C; maximum, minimum, average and night , measured done during an half hour), wind speed (Ws, m/s; average at 10 meters, measured during the 10 last minutes of the half hourly step), peak wind speed (PKW, m/s; maximum speed of wind at 10 meters, measured during 30 minutes), wind direction (Wd, deg at 10 meters measured during an half hour), sunshine duration (Su, h, computed with the global radiation series and the power threshold 120 W/m²), relative humidity (RH, % instantaneous measure at the end of the half-hour) and rain precipitations (RP, mm, 5 cumulative measures of 6 minutes during the half-hour). The data are transposed into hourly values by Météo-France organization.

4.1. Daily case

For this horizon and for all studied models, the years 1971-1987 are the basis of learning and the two years from 1988 to 1989 are dedicated to the test of the prediction. With this horizon, the method based on average, Markov chains, k-NN and Bayesian inferences are tested. For all this methodology the results are equivalent, the error (nRMSE) is close to 25.5% (from 25.1 for Markov chains to 26.13 for the persistence). Without stationarization and exogenous inputs, the two predictors ARMA and MLP are more efficient than other methods; the errors of prediction are smaller than 22% and relatively close. For this first study, where only endogenous data are considered, these two predictors are equivalent and outperform other approaches. If now we make the TS stationary by using k or CSI and seasonal adjustments (k* and CSI*) we note that the error of prediction decreases. The best results are related to the k* and CSI* pretreatments. With these methodologies the errors are reduced by 1.5 points (nRMSE =20.2% for k*and nRMSE =20.3% for CSI*). Indeed, it is necessary to adapt the models and architectures to the new dynamics of the signal. The optimization leads to use the model ARMA(2,2), while for the MLP configuration remains unchanged.

For more details on results of other methods (persistence, Bayesian, KNN, etc.), the reader can refer to our previous work [15,44]. Again, the MLP and ARMA methods appear to be equivalent for d+1. Indeed, with or without the use of seasonal adjustments, it is very difficult to prioritize them. It seems, in the particular case that we just examined, that MLP based results are also convincing than ARMA based results. Regarding the comparison between the two stationary methodologies (k* and CSI*), it is not possible to conclude, averages are not significantly different. However, make stationary the TS improves the prediction error both for ARMA and MLP.

Once finished these first experimentations, we decided to explore the multivariate option. In order to increase the confidence degree of our conclusions we choose to make our test considering two locations: Ajaccio and Bastia (where forecasting is considered to be more difficult). Indeed one of the particularities of the MLP use is based on the possibility to do multivariate regressions. The use of the exogenous data should better model the phenomena. As the errors are respectively 21.5% ± 0.05% and 25.4± 0.2%, we can deduce that the generated error is location-dependent. In addition, we have shown that the use of exogenous variables improved the MLP prediction mainly during winter and autumn (gain of 0.7 point). Similar results are obtained with the PV energy forecasting [44].

4.2. Hourly case

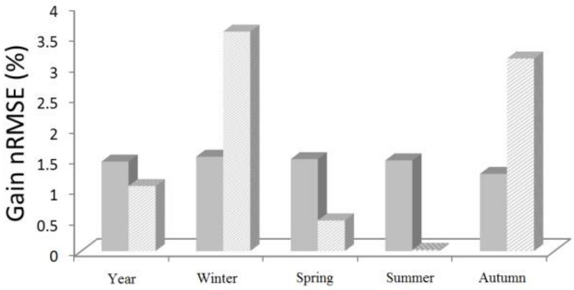
For this horizon the CSI* approach simplifies the MLP architecture: one endogenous input and a maximum of 8 hidden neurons for the five TS studied. But this does not improve the prediction error, so in the following, the stationary mode will not use the periodic coefficients. Performing the same study in the case of ARMA predictions, CSI* and CSI stationarization give similar results. We therefore decided to use only the CSI with these predictors. Note that the clearness index generates less efficient results [45].

In summer, the interest of methods like MLP endo and MLP endo-exo is minimal. This is undoubtedly due to the low probability of occurrence of clouds during this period. A linear process like ARMA seems best suited. We can probably conclude that use of MLP with endogenous and exogenous variables is interesting when the cloud cover is intense (mainly in autumn and winter). In [45] we have shown that the predictors hybridation (ARMA and MLP endo exo) increases the quality of predictions. The method used is based on the following selection rule:

$$if\ \left|\varepsilon^{AR}(t)\right| < \left|\varepsilon^{MLP}(t)\right|\ then\ \hat{X}(t+1) = \hat{X}^{AR}(t+1)\ else\ \hat{X}(t+1) = \hat{X}^{MLP}(t+1) \tag{3}$$

The Figure 1 shows the average gain (computed on the five cities) of nRMSE obtained by the hybrid method compared to the better MLP (grey bars) and the better ARMA (dashed bars). The gain is positive when the hybridization is better than traditional methods.

Fig. 1: mean gain related to the hybrid model compared to the models MLP (grey bars) and ARMA (dashed bars)



The maximum gain is observed in winter (3.8 ± 0.8% better than the ARMA model) and the minimum is in summer, when the hybrid method is as interesting as the ARMA method (gain of 0.02 ± 0.5%). For all sites, it is clear that the hybrid model approximates correctly the global radiation [45]. In previous study [45] we have shown that exogenous data (meteorological measures) can be replaced by estimation of analytic models like the numerical weather prediction model ALADIN [45]. In this context, the results generated by hybrid MLP/ARMA, ALADIN and CSI* should be different. This hybrid model is very interesting: the 10% threshold has been crossed in Marseille. Although summer is the season where the hybrid methodology is the less interesting, all seasons and cities benefit from this hybridization model. We can note that MLP and ARMA are very effective alone in summer period. To resume, use of the hybrid method reduces the error by 11% compared to the prediction done by persistence (mean on the five cities).

In summary, the fact to make stationary the global radiation TS reduces the error by 0.5 ± 0.1% for the five locations studied. The use of ALADIN and of hybridization models shows a real potential and a strong interest. This step allows to increase significantly the quality of the prediction (gain close to 3.5 points). In the end, if we compare this approach with a simple prediction such as persistence, there is a reduction of the prediction error of more than 11%. The methodology of prediction based on CSI, ALADIN MLP and ARMA is certainly complicated to implement, but gives results far superior to those from other tested techniques. We note that for this horizon, the CSI must be used to overcome seasonal variations. In addition, the use of exogenous variables is an added value to the modeling. Forecasts of meteorological variables from ALADIN model offer prediction accuracy. However, the use of meteorological measurements gives also good results, although less efficient. Finally, the combination of all the improvements that we recently proposed amplifies the quality of the prediction.

4.3. 24-hours ahead case

This new horizon studied is the prediction for the next day hour by hour [10,51] of the global radiation profile. Unlike hourly, daily or monthly horizons, this horizon is little discussed in the literature. We may mention the work of Mellit and Pavan [27] which propose to use as input of the prediction tool (MLP) the daily mean values of solar radiation and temperature, and the day of the considered month. To satisfy this prediction horizon, we have considered approaches based on the use of MLP, following conclusions presented earlier in this paper. As a first step, we focus on the endogenous case, and then we will introduce exogenous parameters. The predictor is a MLP like in the previous case, but with multiple outputs (one by hours). Measurements are chronologically positioned in the input vector of MLP. We choose to compare the MLP results with those obtained by methods of persistence and ARMA. The last method we have tested is based on multiple ARMA models which each are dedicated to one particular hour. Note that all these methods are compatible with the use of the clearness index (k and k*) and the clear sky index (CSI and CSI*). Moreover, in h+1 and d+1 horizons, the seasonal adjustments did not show strong superiority. For these reasons, in the next manipulations only k and CSI will be considered. The goal is to find a relatively simple and generalizable methodology taken care of not draw conclusions about data snooping.

We note that sophisticated approaches as ARMA or MLP largely outperform naive model especially in winter. Note also that the best predictions are obtained with the use of the clear sky index (CSI). Contrary to the previous case (h+1 case), the MLP is systematically better than ARMA model. The interest of a hybrid approach seems for this reason not relevant. However, it is possible to integrate exogenous inputs. After several trials, we found that the more interesting data are the hourly pressure and cloudiness of the last day, and the daily average nebulosity of the two last days.

For the h+24 horizon the contribution of exogenous variables is less explicit that for previous case studied. These kind of deep horizons ($\geqslant$ 24 h) modify approach to consider. Thus, this type of prediction is particularly difficult to realize. Search the smoothness of a 24-hours ahead prediction depends on too many parameters to expect to get the same level of results as for horizons h+1 or d+1. We can conclude that it is valuable to make stationary data (nRMSE gain close to 0.5 point). To do this the use of clear sky index is preferable, even if the clearness index gives results almost similar. The CSI allows an nRMSE gain of 0.5 point for ARMA and 0.1 point for MLP related to the k use. The classical approach involving a single MLP with multiple outputs is recommended: nRMSE gain of 0.6 point for k index and 0.4 point for CSI index related to a MLP committee like described in the ARMA case. In the present state of our knowledge, the ratio between performance and complexity induces, to not use exogenous variables (maximal nRMSE gain of 0.6 point in Winter).

4.4. Five minutes case

The originality of this case is the sampling frequency of measurement that is less than the dynamics of cloud occurrence. Thus, in 5 minutes the sky has a high probability of remain identical. Data are available on the PV wall of Vignola laboratory [44]. They cover the period from March 2009 to September 2010.

The installation allows identifying three separate areas: 0 °, 45° SE and 45 °SW tilted at 80° relative to the ground surface.

Unlike in the daily and hourly case this study does not allow concluding that the use of CSI and k are justified. For this tilt and orientation, the theoretical models are limited. In these configurations the solar shield complicated the phenomena. For this reason, CSI, k, CSI* and k* are not used in the following (only raw data). In fact, in the raw global radiation TS, output of MLP corresponds to an improved persistence. As the prediction seems to be a persistence (delay of 5 min), weights related to the first lag are important and other are close to zero.

Simpler tools, accessible with MLP could improve the prediction results. Indeed, the MLP can alone choose its own stationarity, using as input time indexes, which will enable it to establish a regression on the time of the periodic phenomenon. The two time indices used are related to hour of the day and day of the year. The transfer function in the hidden layer which gives the best results is the Gaussian function. The use of time index generates an added value to the quality of the prediction. Results are systematically improved by this tool: nRMSE is reduced by 0.7 point for the SW and S orientations and 0.1% in the SE case. The average gain is greater than 0.5 point, ensuring a real advantage in using this stationarization mode.

Note that for this horizon, the use of ARMA is not relevant because the optimization led us to use an simple AR(1) where the regression coefficient of lag 1 is close to 1. This kind of model is in fact persistence. Like MLP is systematically better than persistence, the hybridization of models is not justified. Moreover, the use of exogenous data does not provide benefit for the prediction. Furthermore there are very few measurements with a sampling near 5 minutes. This kind of prediction process is very complicate to construct. In brief, we have seen in this section that methods used to make stationary the TS are not available for this horizon (nRMSE increased by 1 point). It is more appropriate to use the raw series and not the clear sky or clearness index, but the use of time index is interesting to take into account the seasonality. We may also note that the MLP-based methodology improves outcomes (nRMSE improved to more than 1 point) compared to a simpler approach based on persistence.

5. Conclusion

In all bibliographic items related to the estimation of global radiation, we find that the errors associated with predictions (monthly, daily, hourly and minute) differ from sites and from authors. Methodologies of predictions are usually so different that they are difficult to compare. We present here a methodology of comparison of different predictors developed and tested to propose a hierarchy.. For horizons d+1 and h+1, our results are partly consistent with the literature. Indeed, MLP are adapted and used to make predictions of global radiation with an acceptable error [52] and are also applicable to mountainous areas [53]. Regarding prioritization of ARMA and MLP, the results shown here are different from traditional bibliographic results [26,54,55]. In fact, without stationarity we do not think it is easy to differentiate between ARMA and MLP. Moreover, while ANN by its non-linear nature is effective to predict cloudy days, ARMA techniques are more dedicated to sunny days without cloud occurrences. However, we agree Berhangh et al. [37] with the fact that the use of exogenous variables improves the results of MLP. As in the literature, we found that the relevant approaches in the case of the prediction of radiation were equally in the case of the prediction of PV power [26,56]. Although it is not routinely used in the literature, we believe that persistence can correctly judge the validity of complex technical and we chose as naive predictor. In literature, clear sky model and seasonal adjustments based on periodic coefficients have not often been used with the prediction of global radiation. The views of the results presented here, their investigation looks promising. Finally, for horizons h+24 and m+5, there are still too few studies using the MLP. However as Mellit and Pavan [27] and Chaabene and Ben Ammar [57] we believe and have shown that the MLP were adapted to these situations. In addition, our approach with the use of time index appears to be efficient. In summary, our results are complementary and improve the existing prediction techniques with innovative tools (stationarity, NWP combination, MLP and ARMA hybridization, multivariate analysis, time index, etc.).

Through this work, we have identified some methodologies for the prediction horizon of global radiation. We can conclude that these two types of predictions are relatively equal in the methodology to implement. In Table 10 are listed and summarized TS based methods we recommend for different prediction horizons.

Table 10: summary of the results presented in this paper

Horizons	**stationarity**	**Exogenous data**	**Required predictors**	**difficulty**	***nRMSE***
d+1	CSI*	Measures: *Su.N.RH*	*MLP*	++	23.4%
h+1	CSI	NWP: N. P. RP	Hybrid_MLP+ARMA (>MLP>ARMA>pers)	+++	14.9%
h+24	k	-	MLP multi-outputs (>multiMLP>ARMA>pers)	+	27.3%
m+5	Time index	-	MLP (> ARMA > pers)	+	20.2%

In view of the previous manipulations, we note that the results can be completely different depending on the time horizon. For this reason, we must pay attention to the methods used and the expected results. What should be sought is a simple method to implement, cost effective and workable in several locations: the selection of data and model parameters must be chosen parsimoniously. To conclude this paper, we believe that the establishment of a benchmark in the areas of renewable energy would allow the community to better share, understand and interpret the results: same data, comparisons of models using the same tools RMSE, nRMSE, IC95%, etc. The recent European COST (Cooperation in Science and Technology) initiative called WIRE (Weather Intelligence for Renewable Energies) seems to follow this idea and should be encouraged.

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References

~~[1] Schlink U, Herbarth O, Richter M, Dorling S, Nunnari G, Cawley G, et al. Statistical models to assess the health effects and to forecast ground-level ozone. Environmental Modelling & Software 2006;21:547–58.~~

~~[2] Jenn Jiang H. Policy review of greenhouse gas emission reduction in Taiwan. Renewable and Sustainable Energy Reviews 2011;15(2):1392–402.~~

~~[3] Benghanem M, Mellit A, Alamri SN. ANN-based modelling and estimation of daily global solar radiation data: A case study. Energy Conversion and Management. 2009;50(7):1644–55.~~

[4] Voyant C, Muselli M, Paoli C, Nivet M-L. Optimization of an artificial neural network dedicated to the multivariate forecasting of daily global radiation. Energy 2011;36(1):348–59.

[5] Carl-Jochen W. Hydrogen energy — Abundant, efficient, clean: A debate over the energy-system-of-change. International Journal of Hydrogen Energy 2009;34:1–52.

[6] Darras C, Muselli M, Poggi P, Voyant C, Hoguet JC, Montignac F. PV output power fluctuations smoothing: The MYRTE platform experience. International Journal of Hydrogen Energy 2012;37:14015-14025.

~~[7] Do Sacramento EM, Sales AD, de Lima LC, Veziroglu TN. A solar–wind hydrogen energy system for the Ceará state – Brazil. International Journal of Hydrogen Energy. 2008;33(20):5304–11.~~

[8] Tamer K, Azah M, Sopian K. A review of solar energy modeling techniques. Renewable and Sustainable Energy Reviews 2012;16: 2864-2869.,

[9] Cao JC, Cao SH. Study of forecasting solar irradiance using neural networks with preprocessing sample data by wavelet analysis. Energy 31; 2006:3435-3445.

[10] Chaouachi A, Kamel RM, Ichikawa R, Hayashi H, Nagasaka K. Neural Network Ensemble-Based Solar Power Generation Short-Term Forecasting. World Academy of Science, Engineering and Technology 54;2009..

[11] Brockwell Peter J, Richard A. Davis. Time series: theory and methods. 2nd ed. New York: Springer-Verlag, 1991.

[12] Faraday J, C Chatfield. Times Series Forecasting with Neural Networks: A Case Study. Applied Statistics,1998.

[13] Yakowitz S. Nearest neighbors method for time series analysis, Journal of Time Series Analysis 1987;8:235-247.

[14] Armstrong JS (Ed.). Principles of forecasting: a handbook for researchers and practitioners. Boston; London, Kluwer Academic, 2001.

[15] Paoli, C, Voyant C, Muselli M, Nivet ML. Solar radiation forecasting using ad-hoc time series preprocessing and neural networks. Springer-Verlag, 2009:898:907.

[16] Sharif M, Burn D. Simulating climate change scenarios using an improved K-nearest neighbor model, Journal of Hydrology 2006;325:179-196.

[17] Celeux G, Nakache J. Analyse discriminante sur variables qualitatives, Polytechnica proceeding, Paris, France, 1994.

[18] Diday E, Lemaire J, Pouget J, Testu F. Éléments d'analyse de données, Dunod, 1982.

[19] Muselli M., Poggi P, Notton G, Louche A. First order Markov chain model for generating synthetic “typical days” series of global irradiation in order to design photovoltaic stand alone systems, Energ. Convers & Manage 2011;42:675-687.

[20] Logofet D. The mathematics of Markov models: what Markov chains can really predict in forest successions, Ecological Modeling 2000; 126:285-298.

[21] Sharif M, Burn D. Simulating climate change scenarios using an improved K-nearest neighbor model, Journal of Hydrology 2006;325:179-196.

[22] Yakowitz S. Nearest neighbors method for time series analysis, Journal of Time Series Analysis 1987;8:235-247.

[23] Hamilton J. Time series analysis, Princeton University Press, 1994.

[24] Bourbonnais R, M. Terraza, Analyse des séries temporelles . Application à l 'Economie et à la Gestion , 2 éd., Dunod, Paris, 2008.

[25] Ahmed O, Driss Z, Hanane D, Rachid B. Artificial neural network analysis of Moroccan solar potential , Renewable and Sustainable Energy Reviews 2012;16 :4876-4889.

[26] Mellit AM, Kalogirou S, Hontoria L, Shaari S. Artificial intelligence techniques for sizing photovoltaic systems: A review, Renewable and Sustainable Energy Reviews 2009;13:406-419.

[27] Mellit AM, Pavan A. 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy, Sol. Energ 2010;8::807-821.

~~[28] Hocaoglu F, Gerek O, Kurban M. Hourly solar radiation forecasting using optimal coefficient 2-D linear filters and feed-forward neural networks. Solar Energy 2008;82:714-726.~~

~~[29] Fariba B, Dehghan AA, Faghih AR. Empirical models for estimating global solar radiation: A review and case study. Renewable and Sustainable Energy Reviews 2013;21: 798-821.~~

~~[30] Kalogirou S. Artificial neural networks in renewable energy systems applications: a review. Renewable and Sustainable Energy Reviews 2001;5:373-401.~~

~~[31] Kemmoku Y. Daily insolation forecasting using a multi-stage neural network. Solar Energy 1999;66:193-199.~~

~~[32] Hontoria L, Aguilera J, Zufiria P. Generation of hourly irradiation synthetic series using the neural network multilayer perceptron. Solar Energy 2002;72:441-446.~~

~~[33] Negnevitsky M. An Expert System Application for Clearing Overloads. International Journal of Power and Energy Systems 1995;15:9-13.~~

~~[34] Al-Alawi SM, Al-Hinai HA. An RNA-based approach for predicting global radiation in locations with no direct measurement instrumentation. Renewable Energy 1998;14:199-204.~~

~~[35] Mohandes M, Rehman S, Halawani TO. Estimation of global solar radiation using artificial neural networks. Renewable Energy 1998;14:179–184.~~

[36] Sfetsos A, Coonick AH. Univariate and multivariate forecasting of hourly solar radiation with artificial intelligence techniques. Solar Energy 2000;68:169-178.

[37] Behrang MA, Assareh E, Ghanbarzadeh A, Noghrehabadi AR. The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data. Solar Energy 2010;84:1468-1480.

[38] Kim, Tae Yoon, Kyong Joo Oh, Chiho Kim, et Jong Doo Do. Artificial neural networks for non-stationary time series. Neurocomputing 2004;61:439-447.

[39] Zhang G. Peter, Min Qi. Neural network forecasting for seasonal and trend time series. European Journal of Operational Research 2005;160:501-514.

[40] Mueller RW, Dagestad KF, Ineichen P, Schroedter-Homscheidt M, Cros S, Dumortier D, R. Kuhlemann R, et al. Rethinking satellite-based solar irradiance modelling: The SOLIS clear-sky module. Remote Sensing of Environment 2004;91:160-174.

[41] Badescu V. Modeling solar radiation at the earth’s surface: recent advances. Springer, 2008.

[42] Voyant, C. Prédiction de séries temporelles de rayonnement solaire global et de production d'énergie photovoltaïque à partir de réseaux de neurones artificiels. Thesis, Université de Corse (2011).

[43] Cococcioni, M, D'Andrea E, Lazzerini B. 24-hour-ahead forecasting of energy production in solar PV systems. In 2011 11th International Conference on Intelligent Systems Design and Applications (ISDA) 2011:1276 -1281.

[44] Meita R, Abudureyimu A, Nagasaka K. Mapping of solar energy potential in Indonesia using artificial neural network and geographical information system. Renewable and Sustainable Energy Reviews 2012;16:1437-1449.

[45] Bosch J, Lopez G, Batlles F. Daily solar irradiation estimation over a mountainous area using artificial neural networks. Renewable Energy 2008;33:1622-1628.

[46] Reddy K. Solar resource estimation using artificial neural networks and comparison with other correlation models. Energy Conversion and Management 2003;44:2519-2530.

[47] Amit KY, Chandel SS. Tilt angle optimization to maximize incident solar radiation: A review. Renewable and Sustainable Energy Reviews 2013;23:503-513.

[48] Benghanem, Mohamed, Adel Mellit. Radial Basis Function Network-based prediction of global solar radiation data: Application for sizing of a stand-alone photovoltaic system at Al-Madinah, Saudi Arabia. Energy 2010;35:3751-3762.

[49] Chaabene M, Benammar M. Neuro-fuzzy dynamic model with Kalman filter to forecast irradiance and temperature for solar energy systems. Renewable Energy 2008;33:1435-1443.

~~[50] Almonacid F, Rus C, Hontoria L, Muñoz FJ. Characterisation of PV CIS module by artificial neural networks. A comparative study with other methods. Renewable Energy 2010;35:973-980.~~

~~[51] A. Azadeh, A. Maghsoudi, et S. Sohrabkhani, An integrated artificial neural networks approach for predicting global radiation. Energy Conversion and Management 2009;50:1497-1505.~~

~~[52] Jiang Y. Prediction of monthly mean daily diffuse solar radiation using artificial neural networks and comparison with other empirical models. Energy Policy 2008;36:3833-3837.~~

~~[53] Mellit A, Benghanem A, Kalogirou SA. An adaptive wavelet-network model for forecasting daily total solar-radiation. Applied Energy 2006;83:705-722.~~

~~[54] Cao S, Cao J. Forecast of solar irradiance using recurrent neural networks combined with wavelet analysis. Applied Thermal Engineering 2005;25:161-172.~~

~~[55] Mellit A, Benghanem M, Arab AH, Guessoum A. A simplified model for generating sequences of global solar radiation data for isolated sites: Using artificial neural network and a library of Markov transition matrices approach. Solar Energy 2005;79:469-482.~~

~~[56] Sözen A, Arcaklioğlu E, Özalp M. Estimation of solar potential in Turkey by artificial neural networks using meteorological and geographical data. Energy Conversion and Management 2004;45:3033-3052.~~

~~[57] Reddy K, Ranjan M. Solar resource estimation using artificial neural networks and comparison with other correlation models. Energy Conversion and Management 2003;44:2519-2530.~~