Wind and Solar Forecasting for Renewable Energy System using SARIMA-based Model

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Abstract

In order to completely fulfill a datacenter power demand, one important issue is to determine and investigate a reasonable sizing for Hybrid Renewable Energy System (HRES). Usually, in the context of datacenter renewable power supply, the energy production is hybrid and it consists of wind and solar energy production associated with battery and hydrogen energy. To design the electrical energy system, one needs to forecast weather conditions (solar radiation, wind speed) in order to evaluate the energy production yearly. The aim of this paper is to propose a SARIMA-based model for a particular renewable energy system. Indeed, thanks to the wind turbine and solar panel models, it is possible to optimize the overall cost of the global energy system. We finally validate the proposed model on actual data.

1 Introduction

The twentieth century witnessed a boom in the number of data centers around the world driven by a rapid growing demand for Cloud services. Consequently, the energy footprint of the IT sector has increased exponentially and reached unprecedented levels. It is, actually, estimated to consume approximately 7% of global electricity in 2007 [1]. Furthermore, in 2016, statistics shows that data centers demand reached 91 billion kWh of electricity which is twice more than New York city consumption [2].

In this scenario, with climatic conditions going for drastic reversals, a global alert concerning the environment, the greenhouse gas (GHG) emissions, air pollution, social concerns and other energy security issues [3, 4] is raised. Consequently, the attention of many government and researchers

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around the world has shifted to find a new alternative energy sources that matches with the environment. One of the most popular solution is the utilization of renewable energy sources as they have been established to be sustainable, economical, nature friendly, abundant, non-polluting and renewable [5, 6]. In fact, the European Technology Platform for electricity networks of the future, known as ETP Smart grid expected that, by 2020, approximately 34% of the total electrical consumption will come from renewable energy and will have gone more than that by 2035 [7]

Nevertheless, considering the intermittent nature of solar radiation and wind, and the high capital and operational costs of solar panels and wind turbines with the necessary energy storage devices, forecasting the next-day outputs of the power generation systems becomes a major issue to evaluate the appropriate power architecture sizing. Thus, a lot of research teams around the world and particularly in the coastal area [8, 9, 10] mobilize their efforts on either solar prediction or wind speed prediction. As a result, many forcasting methods have been developed by experts around the world [11, 12, 13] that could be classified following their approach and the time scale of prediction (e.g., physical approach such as Numeric Weather Prediction (NWP)). This model solves complex mathematical models using weather data like temperature, pressure, surface, etc. NWP is usefulness for medium to long-term forecasts ($>$ 6h ahead) [14, 15]. Also, statistical approach which is based on training the measurement data by using the difference between the predicted and the actual wind speeds in immediate past to tune model parameters such as neural network (NN) based methods, and Time-Series based models like ARMA [16], ARIMA [17], Grey Predictors, Linear Predictions, etc. Finally, a hybrid approach exists with a combination of different approaches like combining short-term and medium-term models or mixing physical and statistical approaches [18, 19, 20].

This paper focuses on applying a statistic approach for forcasting wind speed and solar radiation on two different location, Los Angeles and Chicago in the USA. Considering the history of meteorological conditions in terms of solar radiation and wind speed at the two selected sites and the mathematical models of wind turbine and solar panels, one can compute the electrical production during the time horizon considered. Thus, based on this amount of energy production, the sizing of a hybrid renewable energy system composed of wind turbines, solar panels, battery and hydrogen storage systems has to be designed to completely supply a data center whose demand has a peak power less than 500 kW.

The remainder of the paper is organized as follows. Section 2 presents the methodology used in order to forecast weed speed and solar irradiation to be able to designed a hybrid renewable energy systems supplying a datacenter. This sizing is briefly explained in Section 3. Then, the obtained results are presented and discussed in Section 4. A conclusion and perspectives are given in Section 5.

2 Forecasting Methodology

Before presenting the whole methodology, we start by introducing the type of data as well as their locations. We here dispose of two types of data: solar radiation and wind speed. The latter could be obtained from various databases online such as the national solar data base (NSRDB) [21], the Modern-Era Retrospective analysis for Research and Applications (MERRA2) [22], the wind prospector from the National Renewable Energy Laboratory (NREL) [23]. In our case, the data are obtained from NSRDB AND NREL. Recall that the aim of this paper is to propose a statistical approach for wind and solar forecasting. For that purpose, based on a review and results obtained by different researchers mentioning the accruacy of the ARIMA model [18, 17, 24, 25], we have selected the SARIMA model [26, 27]. In order to verify the robustness of the SARIMA approach on our application, we will apply the methodology on two distinct locations having different characteristics.

2.1 SARIMA model

ARIMA is a statisctical approach widely used in today's world since the evolution of sophisticated statistical software package. ARIMA has four major steps in model building- Identification, Estimation, Diagnostics & Forecast. Then, the general scheme for ARIMA model is translated by:

1. Identification of the model structure.
2. Application of autocorrelation function (ACF) and partial autocorrelation function (PACF) in order to identify the orders of the ARMA model. The parameters of the model are estimated by a maximum likelihood (ML) function
3. Testing the goodness of fit on the estimated model residuals
4. Using the estimated model for forecasting.

ARIMA model uses the historic data and decomposes it into autoregressive (AR), Integrated (I) indicates linear trends or polynomial trend and Moving Average (MA) indicates weighted moving average over past errors. Therefore, it has three model parameters AR(p), I(d) and MA(q) all combined to form ARIMA(p, d, q) model where:

- p = order of AR
- q = order of MA
- d = order of I (differencing)

The multiplicatif Seasonal ARIMA model namely SARIMA is actually a variation of the classical ARIMA model. In order to take into account the seasonal effect of the irradiation and the wind speed, this model is generally written as SARIMA(p,d,q)(P,D,Q) where, as in the ARIMA model, p, d, q and P, D, Q are non-negative integers that refer to the polynomial order of the AR, I, MA parts of the non-seasonal and seasonal components of the model, respectively. Mathematically, the SARIMA model is defined as in (1)

$$\phi_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D x_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{1}$$

Where: x_t is the forecast variable (i.e., solar radiation), $\phi_p(B)$ is the regular AR polynomial of order $p()$, $\theta_q(B)$ is the regular MA polynomial of order $q()$, $\Phi_P(B^s)$ is the seasonal AR polynomial of order $P()$, $\Theta_Q(B^s)$ is the seasonal MA polynomial of order Q, ∇^d is the differentiating operator that eliminate the non-seasonal non-stationarity, ∇_s^D is the seasonal differentiating operator that eliminate the seasonal non-stationarity, B is the backshift operator, which shift one point in time the observation x_t (i.e., $B^k(x_t) = x_{t-k}$) and finally ε_t follows a white noise process and s defines the seasonal period. These polynomials are described mathematically in Equations (2):

$$\begin{aligned}
\theta_q(B) &= 1 - \sum_{i=1}^{q}\theta_i B^i & \Theta_Q(B^s) &= 1 - \sum_{i=1}^{Q}\Theta_i B^{s,i} \\
\phi_p(B) &= 1 - \sum_{i=1}^{p}\phi_i B^i & \Phi_P(B^s) &= 1 - \sum_{i=1}^{P}\Phi_i B^{s,i} \\
\nabla^d &= (1-B)^d & \nabla_s^d &= (1-B^s)^D
\end{aligned} \tag{2}$$

In order to get the model that fits the best the data, the Akaike Information Criterion (AIC) is a statistic measure to compare them. In fact, the AIC rewards models for a good fit and penalize others for complexity. It could be written as:

$$AIC = 2k + \ln\left(\frac{RSS}{n}\right) \tag{3}$$

with k the number of free parameters, n the total number of observations equal to 468 and RSS is the residual sum of squares.

Finally, using the obtained valid model, one can proceed to the forecasting of the wished period.

2.2 Evaluation of the forecasting performance

The forecasting model is constructed on time series of solar radiation and wind speed for a duration of 9 years weekly (which means 468 values). Once the models are formulated, they are used to forecast wind speed and solar radiation for the last two years . Afterwards, the averages of the statistics for the 2 years forecasting results are computed to analyze the models' accuracy. Several measurement statistics can be used to examine the forecast accuracy of different models. Mean absolute percentage error (MAPE) is used very often to evaluate the performance of the forecasting model. The above-mentioned statistical quantities are computed as in (4):

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{x_t - \hat{x}_t}{x_t} \right| \tag{4}$$

where $\hat{x}_t$ is the forecast value.

3 Hybrid renewable energy system sizing

The aim of this work is to determine an the optimal size of the stand-alone hybrid renewable energy sources (HRES) to fulfill the energy demand of the data center. These electrical sources are divided into 2 different subsystems:

- The primary sources: consist in providing the basic power to supply the data center and are composed of photovoltaic panels and wind turbines.
- The secondary sources: are the back up power to supply the data center in times of need and are composed of batteries and fuel cells.

As the datacenter should be autonomous in terms of energy consumption, the totality of the energy comes from primary sources. Moreover knowing that the primary sources operate as intermittent sources in time, we have to balance the lack of energy production (for example in the winter) by an over production (summer) during the year. To achieve this balance, the secondary sources (storage sources) are divided following the type of storage and operate as follows:

- Long-term storage: where the day of overproduction will balance the days of underproduction. The electrical resources used in this case is the hydrogen system
- Short-term storage: where the hours of overproduction will balance the hours of underproduction during the same day (fluctuations between day and night). It means that the production will be smoothed over the day. The electrical resources used in this case is the batteries.

Using the data center demand and the meteorological data downloaded, one needs to understand the models of the first subsystem in order to proceed to the sizing of the primary sources.

3.0.1 Solar Model

To model the relation between the irradiation data and the output power P_pv of the PV panels, a widely used model [28, 29, 30, 31, 32] is described by Equation (5):

$$P_{pv} = I \times A_{pv} \times \eta_{pv} \tag{5}$$

where, I is the hourly solar irradiance in kW/m^2, A_{pv} is the area of the PV panels in m^2, and η_{pv} is their efficiency.

3.0.2 Wind model

The model of the output power of one wind turbine generator P_w that follows the power curve is shown in Figure 1 [33]. So, the turbine starts generating power at the "cut-in" wind speed v_{ci}. Then, the generated output power increases with the increase of wind speed from the "cut-in" v_{ci} to the rated wind speed v_r. When the wind speed varies between the rated wind and the "cut-out" wind speed v_{co}, which is the maximum wind speed value at which the turbine can correctly work, the turbine produces a constant or "rated power". Once the wind speed goes beyond the "cut-out" speed, the turbine stops generating for safety reasons.

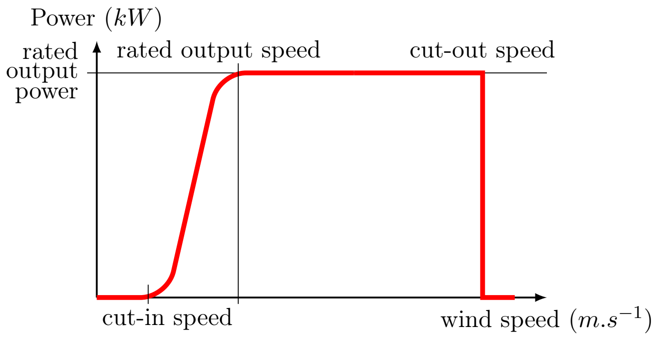


Figure 1: Ideal wind turbine power output

Many other papers, such as [34, 35, 36, 32], have adapted this mathematical model of the wind turbine power output that can be written as in Equation (6):

$$P_w = \begin{cases} 0 & \text{if} \quad v(t) \leq v_{ci} \text{ or } v(t) \geq v_{co} \\ P_r \dfrac{v(t) - v_{ci}}{v_r - v_{ci}} & \text{if} \quad v_{ci} < v(t) < v_r \\ P_r & \text{if} \quad v_r < v(t) < v_{co} \end{cases} \tag{6}$$

where $v(t)$ is the wind speed $(m.s^{-1})$ at any time t (s) and P_r is the nominal power of the wind turbne.

4 Results and discussions

The data representing the solar radiation and wind speed were measured on an hourly scale from January 2004 till December 2012 (more than 6 years) in two different location. To be more precise, the endogenous data of the solar radiation and wind speed time series were measured at Chicago (Latitude: 41.810539, Longitude: -87.643127, Time Zone: -6) and at Los Angeles (Latitude: 34.57, Longitude: -118.02, Time Zone: -8). Then, in order to obtain weekly values, we calculated averages per groups of 168 values (168 hours per week). Finally, we have obtained time series of 52 value per year, i.e., 468 values during the nine years. Figures 4d and 4c showed this distribution respectively for solar radiation and wind speed in Los Angeles. The first nine years have been used to setup our models and the last two years to test them. The model has been implemented using R programming language.

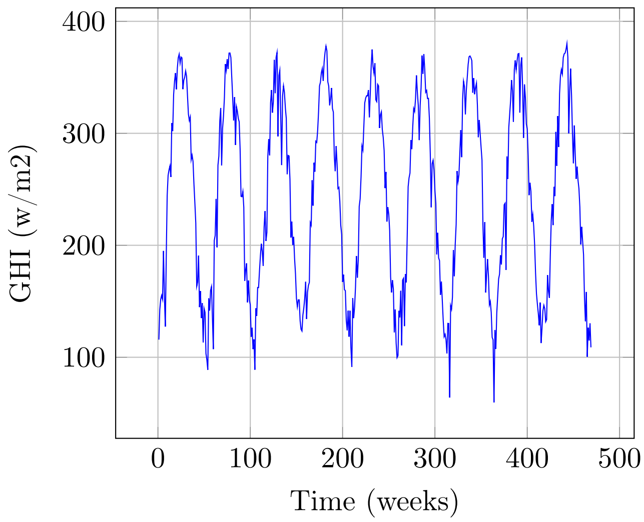


Figure 2: Weekly solar radiation distribution in Los Angeles

4.1 Models validation

Based on Figure 4d, the measured solar radiation from 2004 till 2012 is quite seasonal. In fact, the data starts from the first week of January till the last week of December. Each year, the pic of solar radiation is in July that corresponds to the summer season where days are quite long. Contrariwise, the lowest values are obtained in December or in January. This period

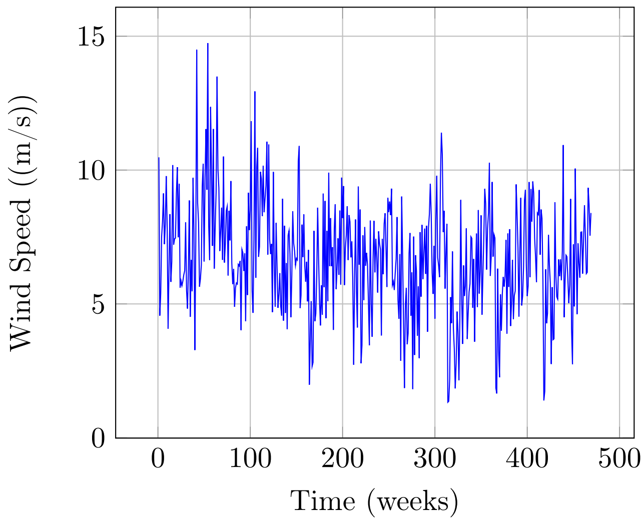


Figure 3: Weekly wind speed distribution in Los Angeles

matches with the winter where days are short. Thus, the solar distribution is intrinsically seasonal and periodic which validates the choice of the SARIMA model.

In Figure 4c, the data also starts from the first week of January till the last week of December. Moreover, it shows a random distribution where data varies from $3\,m/s$ till $14.8\,m/s$. This series presents a seasonality that could be well seen especially starting from the week 150. The wind speed is quite low in the winter and increases with the oncoming of summer corresponding to the thermal hot wind of Los Angeles. Nevertheless, the wind can vary from one year to another so we cannot confirm the periodicity.

Table 1: Comparison of the statistic criterion AIC for wind speed in both Chicago and Los Angeles

DATA	***SARIMA Configurations***	***AIC***
Chicago	SARIMA(21,0,21)(1,1,0)	1441,393
	SARIMA(11,0,14)(1,1,1)	1359,254
	SARIMA(11,0,14)(0,1,1)	1358,813
	SARIMA(18,0,18)(0,1,0)	1498,97
Los Angeles	SARIMA(9,0,19)(1,1,0)	1886,61
	SARIMA(6,0,6)(1,1,1)	1844,582
	SARIMA(6,0,6)(0,1,1)	1839,007
	SARIMA(9,0,0)(0,1,0)	2006,21

In order to obtain the model that fits the best the data, different configurations of SARIMA have been applied on the distributions for the two locations. In each set, 4 seasonal configurations have been applied such as the seasonal polynomial AR and MA respectively $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are set as explained in Table 1

Table 2: Comparison of the statistic criterion AIC for solar radiation in both Chicago and Los Angeles

DATA	***SARIMA Configuration***	***AIC***
Chicago	SARIMA(10,0,9)(1,1,0)	4162,49
	SARIMA(4,0,18)(1,1,1)	4075,66
	SARIMA(4,0,18)(0,1,1)	4075,32
	SARIMA(10,0,9)(0,1,0)	4283,52
Los Angeles	SARIMA(20,0,14)(1,1,0)	3796,42
	SARIMA(13,0,14)(1,1,1)	3735,64
	SARIMA(13,0,14)(0,1,1)	3733,59
	SARIMA(13,0,20)(0,1,0)	3884,346

Based on results given in Tables 1 and 2 in the two different cities, with completely different characteristics, one can see that the best AIC obtained is the one of the model configuration SARIMA(p,d,q)(0,1,1) for both solar radiation and wind speed data. For instance, The SARIMA model$(6,0,6)(0,1,1)$ is written during a period of $s = 52$ as in Equation (7)

$$(1-\phi_1 B^1 - \phi_3 B^3 - \phi_6 B^6)x_t = (1-\Theta_1 B^s)(1-\theta_1 B^1 - \theta_3 B^3 - \theta_3 B^3 - \theta_6 B^6)\varepsilon_t \tag{7}$$

Thus, only the latter is maintained as valid models to be used in the forecasting of the solar radiation and wind speed for a duration of two years.

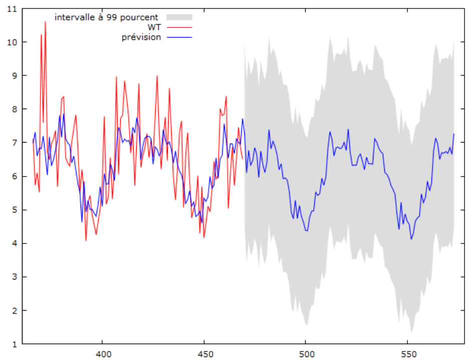
4.2 Forecasting evaluation

Now coming back to the objective to predict the future meteorological data with the valid SARIMA$(p,d,q)(0,1,1)$ model obtained in the section before, the results are shown in Figure 4. Moreover, to investigate the model sufficiency, we summarize the useful statistics about the forecasting results in Table 3 by computing the mean absolute percentage error of all the tested weeks.

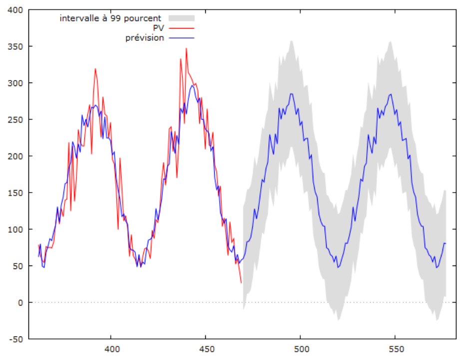
The forecasting model is applied on four years where it compares with the last two years 2011 and 2012 and continue the forecasts till 2014 weekly.

Based on the solar radiation prevision in Figures 4b and **??**, the forecasting curves in blue are quite fitting the real data of the years 2011 and 2012 and follow the seasonality. Moreover, with a MAPE equal to 7 and 15.60 for the two sites Los Angeles and Chicago respectively, the SARIMA model is quite validated and accurate.

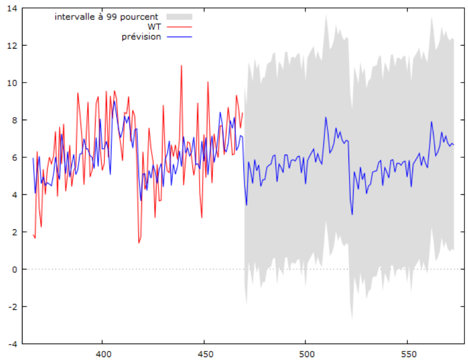
Figures 4a and 4c show the wind speed forecasting starting from 2011 till 2014. The forecasting curves in blue is following the trend of the real data



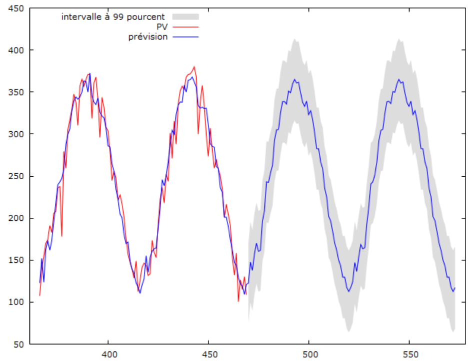
(a) Wind speed in Chicago



(b) Solar radiation in Chicago



(c) Wind speed in Los Angeles



(d) solar radiation in Los Angeles

Figure 4: Forcasting results of the wind speed and solar radiation for Chicago and Los Angeles

of the years 2011 and 2012. Nevertheless, the the 99% confidence interval is quite large and indicates high variability. Thus, these rates should be interpreted with the noise variance estimated. The SARIMA model applied on the wind speed in these two cities, Los Angeles and Chicago, is not as precise as the solar forecasting.

Finally, recall that all interpretations and conclusions presented in this paper are based on data available for the specific areas.

5 Conclusion

This paper presents a comparison among four distinct solar radiation and wind speed generation forecasting models. It is shown that in general, SARIMA model is quite good in the forecasting of the solar radiation during years and fits very well the data because of their seasonal distribution. We also pointed out that the performance of the used model in forecasting the solar during the years is more precise than the ones for the wind speed

Table 3: The mean absolute percentage error of the used methods

Data	Locations	Methode	MAPE
Solar radiation	LA	SARIMA(4,0,18)(0,1,1)	7,03
	Chicago	SARIMA(11,0,14)(0,1,1)	15,60
Wind Speed	LA	SARIMA(6,0,6)(0,1,1)	29,83
	Chicago	SARIMA(13,0,14)(0,1,1)	12,54

which degrades noticeably for long term previsions. It is hence important to predict wind speed variation as precisely as possible. This shows the interest to consider other models or characteristics such as Markov Switching ARMA [37] to improve the precision of the results in order to get an optimal sizing for the hybrid renewable energy system supplying a datacenter power demand.

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