

Recursive Estimation Methods to Forecast Short-Term Solar Irradiation

A. Martín and Juan R. Trapero

Abstract Due to modern economies moving towards a more sustainable energy supply, solar power generation is becoming an area of paramount importance. In order to integrate this generated energy into the grid, solar irradiation must be forecasted, where deviations of the forecasted value involve significant costs. Intermittence, high frequency, and nonstationary are common features of solar irradiation data that have attracted the interest of numerous researchers from different disciplines. In fact, complex methods based on artificial intelligence have been typically used to address this problem. Nonetheless, adequate benchmarks have not been employed to justify such utilization. The objective of this work is to analyze the Holt–Winters (HW) method to forecast solar irradiation at short term (from 1 to 6 h). At the best of our knowledge, this methodology, which belongs to the family of the exponential smoothing methods and is widely used in industry applications ranging from supply chain demand forecasting to electricity load energy forecasting, has not been fully exploited in solar irradiation forecasting. Additionally, in case the accuracy achieved by the Holt–Winters method is not enough, still it can be utilized as a competitive benchmark given its feasible implementation. The Holt–Winters method performance is illustrated by forecasting two time series. Firstly, global horizontal irradiation (GHI) data have been chosen since forecasting GHI is a crucial part in systems based on photovoltaic (PV) energy conversion. Fluctuations of GHI due to passing clouds at short timescales (seconds and minutes) lead to high variability of power output from PV plants that can strain the grid due to voltage-flicker and balancing issues. Furthermore, direct normal irradiation (DNI) data are also forecasted given the role of main fuel that DNI plays in solar concentrator technologies such as solar

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thermal (CSP) and concentrated photovoltaic (CPV) power plants. Both solar irradiation data series have been hourly created from 1-minute irradiance measurements that were collected from ground-based weather stations located in Spain.

Keywords Forecasting methods, Recursive estimation methods, Solar irradiation

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1 Introduction

The increasing investment in renewable energy by developing countries is essential to guarantee immediate answers both to the energy supply crisis with high and fluctuating prices of crude and to the diversification of energy supplies, to reduce the external dependence on foreign oil, gas, and coal. This gives a unique possibility for a major move towards no carbon energy sources and at the same time a decrease in external dependency as well as an improvement of efficiency in electricity generation. Thus, solar power generation becomes an area of paramount research, in particular in countries where energy policies are based on fossil fuels, which are increasingly scarce resources. Reliable short-term forecast information of the components of solar radiation is required to achieve an efficient use of fluctuating energy output from photovoltaic (PV), concentrated photovoltaic (CPV), and solar thermal (CSP) power plants. Electricity companies and transmission systems operators need to be adjusted to the expected load profiles, where forecast errors in the fluctuating input from solar systems lead to significant costs [1, 2].

Intermittence, high frequency, and nonstationary are common features of solar irradiation data that have attracted the interest of numerous researchers from different disciplines. Numerical weather prediction models (NWP), which are based on physical laws of motion and conservation of energy that govern the weather, are operationally used to forecast the evolution of the atmosphere up to 15 days ahead. Although NWP models are powerful tools to forecast solar radiation at places where ground data are not available [3], they pose significant limitations. Global NWP models are limited by its coarse spatial resolution. In order to

overcome this limitation, the downscaling by mesoscale models, which are also named Limited Area Models (LAM) or regional models, allows to derive improved site-specific forecasts. LAM models run for the short-range horizon up to 72 h, and although horizontal resolution of mesoscale models has increased rapidly during the last few years, nowadays, details of complex physical processes near the surface cannot be resolved by parameterization equations due to their small-scale features such as cloud cover genesis and variability. Another limitation of NWP models is the temporal resolution. The time step of internal calculations in NWP models (on the order of minutes) is usually higher than the temporal resolution of the output variables, which is normally of 1 h for mesoscale models and from 3 to 6 h for global models. These temporal output intervals are not suitable to assess, for instance, the time-varying cloud cover evolution and solar irradiation at ground level, which are essentials for predicting ramp rates and ranges of variability for solar power plants.

Satellite-derived solar radiation has also become a useful tool for quantifying solar irradiation at ground surface for large areas and over potential emplacements where previous ground-based measurements are not available [4]. Satellite images corresponding to the same area can be superimposed to analyze the time evolution of air mass in an image pixel or in a certain geographical area. The radiance values recorded by the radiometer of the satellite can vary according to the state of the atmosphere, from clear sky to overcast conditions. In this sense, satellite images give information of the cloudiness at a given time and site [4]. Cloud cover and aerosols have the strongest influence on solar irradiation at ground level. Both parameters show a strong variability in time and space, and modeling cloud structure evolution at a given time is an essential task for solar irradiation forecasting. The cloudiness is defined by the radiance measurements of the satellite radiometer as the cloud index, a cloud reflectance-dependent parameter [5, 6]. The spatial resolution depends on the sensitivity of the radiometer, and the time resolution depends on the time interval between two consecutive images. The geostationary satellites can offer a spatial resolution of up to 1 km and a temporal resolution of up to 15 min. The main limitation from the satellite perspective is setting an accurate radiance value under clear sky conditions and under dense cloudiness from every pixel and every image. Another limitation from satellite images comes from algorithms developed for estimating the solar irradiation that are classified as statistical or empirical models [7, 8]. These algorithms do not need accurate information of the parameters that model the solar radiation attenuation through the atmosphere and are based on simple statistical regression between satellite information and surface measurements. Therefore, the satellite statistical approach needs ground-based solar data. The coarser the observed network, the higher the uncertainty of the satellite-derived solar irradiation data.

Ground-based observations as sky imaging techniques fill the intra-hour and sub-kilometer forecasting gap of NWP models regarding cloud cover over solar power plants. Nonetheless, forecast horizons are limited to very short term, ranging from 5 to 25 min ahead [9]. Comparing with satellite-derived solar irradiation data, sky images offer higher spatial and temporal resolution, but only very short

deterministic forecast horizons are feasible using the sky imagery technique due to cloud variability at the fine spatial scale observed.

The aforementioned limitations have placed time series analysis on local weather stations as the dominated methodology in relation to short-term forecasting horizons [1]. The techniques employed range from artificial intelligence algorithms [10] to classical ARIMA modeling [1, 11]. Despite the fact that a high number of publications propose complex algorithms to tackle the solar irradiation forecasting problem from different statistical approaches as stochastic learning methods [12], it is interesting to note that traditional well-known forecasting techniques as the Holt–Winters (HW, [13]) method has remained overlooked. Holt–Winters technique belongs to the family of exponential smoothing methodologies [14, 15]. In particular, HW is indicated when seasonality component is observed in the data, as it is commonly found in solar irradiation variables. Only two recent works were found related to this approach. On the one hand [16], employed the HW in order to improve the control of grid-connected power systems. In this case, the forecasting horizon was both daily and weekly. On the other hand [17], employed an extension of the exponential smoothing family developed in a state space framework for high-resolution (5 min) solar irradiation time series. Unlike those references, this work investigates the HW method to forecast solar irradiation at short term (from 1 to 6 h), where short-term forecasting horizon is defined according to [18].

The main benefits of HW over other sophisticated approaches are: (1) no need of expert hands to identify, interpret, and implement models and (2) no need of expensive software. These reasons have made exponential smoothing methods a forecasting tool widely used in the industry [15].

In order to illustrate the performance of the proposed model, two hourly time series as global horizontal irradiation (GHI) and direct normal irradiation (DNI) have been constructed from 1-minute ground-based irradiance series. GHI has been selected for this study given that fluctuations of GHI due to passing clouds at short timescales (seconds and minutes) lead to high variability of power output from PV plants. This variability may strain the grid as a consequence of voltage-flicker and balancing issues. Additionally, DNI is also a very relevant component of the total solar irradiation for solar concentrators [12], although it is more sensitive to sky disturbances as cloud cover, aerosol content, water vapor, carbon dioxide, and ozone. A comparative performance analysis between both time series will also be provided. Solar irradiation data were collected from weather stations located in Spain.

In summary, the results show that the HW method can on average reduce the forecast errors to about 38% with respect to the persistence technique for the particular case of the GHI series and around 20% for the DNI series.

The article is organized as follows: in Section 2, the case study design is presented. This section includes the description of the study area and the observational data. Section 3 describes the HW model and other typical forecasting benchmarks. Section 4 explores the experimental results. Finally, main conclusions are drawn in the “Conclusion” section.

2 Case Study

2.1 Dataset Description

Various observational datasets were used to highlight the short-term variability of solar radiation observed at the Earth's surface. Hourly time series of solar irradiation data (Whm^{-2}) provided the basis for the Holt–Winters technique in order to validate its reliability as a forecasting tool at short-term periods (from 1 to 6 h).

All data used in this study were provided by the Institute for Concentration Photovoltaics System (ISFOC), located in Puertollano, Ciudad Real (south-middle of Spain). ISFOC is a research center focusing on concentrated photovoltaic technology (CPV) and has installed 1,1 MW of concentrated photovoltaic energy (CPV) and 5 automatic weather stations in Castilla-La Mancha to measure solar radiation.

Solar irradiance measurements (Wm^{-2}) were recorded every 1 min by a set of solar sensors such as thermopile pyranometers and pyrhemimeters, which complied with the international standards of Baseline Surface Radiation Network (BSRN, [19]). Solar data were stored by an automatic acquisition system, and solar sensors were cleaned every day at dawn to minimize the solar radiation extinction caused by dust deposition on their glass domes.

Hourly series of solar irradiation data (Whm^{-2}) were constructed for this study from 1-minute ground-based solar irradiance data (Wm^{-2}), which were recorded between January 2009 and December 2011 by the weather station that ISFOC has sited at 38.67°N , 4.15°W , and 687 m (asl).

2.2 Global Horizontal Irradiation Data

Solar irradiance is defined as the solar power per area (Wm^{-2}). Solar irradiation is defined as the solar energy per area resulting from the solar power integrated over a time period, which was defined 1 h for this study (Whm^{-2}). Global horizontal irradiation (GHI) is the solar energy on a horizontal surface and is the sum of the direct normal irradiation (DNI) projected onto the horizontal surface (DHI) and the diffuse horizontal irradiation (DiffHI). Diffuse irradiation refers to all the solar radiation coming from the sky except the DNI.

Global and diffuse irradiances (Wm^{-2}) were measured by a first-class pyranometer according to the international standards of BSRN [19]. It comprises a multi-junction wire-wound thermopile glued to the back of the sensor disc. Mounting the pyranometer on a horizontal plane, the solar radiation flux density (Wm^{-2}) from a field of view of 180° can be measured to obtain the global horizontal irradiance. Diffuse horizontal irradiance was measured shading the pyranometer on a horizontal plane from the direct normal beam and the circumsolar

irradiance using a shade ball. A two-axis sun-tracking system was needed to measure diffuse horizontal and direct normal irradiances.

2.3 *Direct Normal Irradiation Data*

Direct normal irradiation (DNI) is the solar energy coming directly from the solar disc and the circumsolar irradiation within approximately 2.5° of the sun center. Direct normal irradiance (Wm^{-2}), also called direct normal beam, was measured by a first-class pyrheliometer according to the international standards of BSRN. It comprises a multi-junction wire-wound thermopile at the base of a tube. The full opening field of view is 5° . The inside of the tube is filled with dry air at atmospheric pressure and sealed at the viewing end. Pyrheliometer was mounted on a two-axis tracker for aiming the tube directly at the sun.

2.4 *Exploratory Analysis*

Our dataset consists of hourly solar irradiation (GHI and DNI) series. These series represent the solar energy integrated over a 1-h period (Whm^{-2}) from 1-minute measured irradiance data (Wm^{-2}) between January 2009 and December 2011. In total, a dataset of 26,280 observations is available. For example, Figure 1 depicts two months of hourly solar irradiation. Upper and lower plot shows the GHI (solid line) and DNI (dashed line) measured in a winter month (January) and a summer month (July) of the same year (2011), respectively. It is interesting to note that a seasonal component can be observed in each month, although the seasonal shape is different in terms of period¹ and amplitude. In this sense, the amplitude of the seasonality in July is almost constant, whereas the amplitude variability in January is more evident. In fact, this variability is more noticeable for the DNI due to its higher sensitivity to atmosphere conditions. In addition, the number of hours where the solar irradiation is different from zero is higher in summer than in winter.

Table 1 shows some descriptive statistics corresponding to the dataset ranging from January 2009 to December 2011. Since the properties of solar irradiation are time-varying, i.e., the solar radiation is greater in summer than in winter, the statistics have been broken down per month. The first and second column represents the mean and standard deviation of the DNI and GHI. It should be pointed out that the DNI mean and standard deviation are higher than its GHI counterpart. Units in Table 1 have been represented in terms of solar irradiation (Whm^{-2}) for the purpose

¹ Although the seasonality period is 24 hours the whole year, we refer to differences of period to the number of hours during a day that solar irradiance is different from zero.

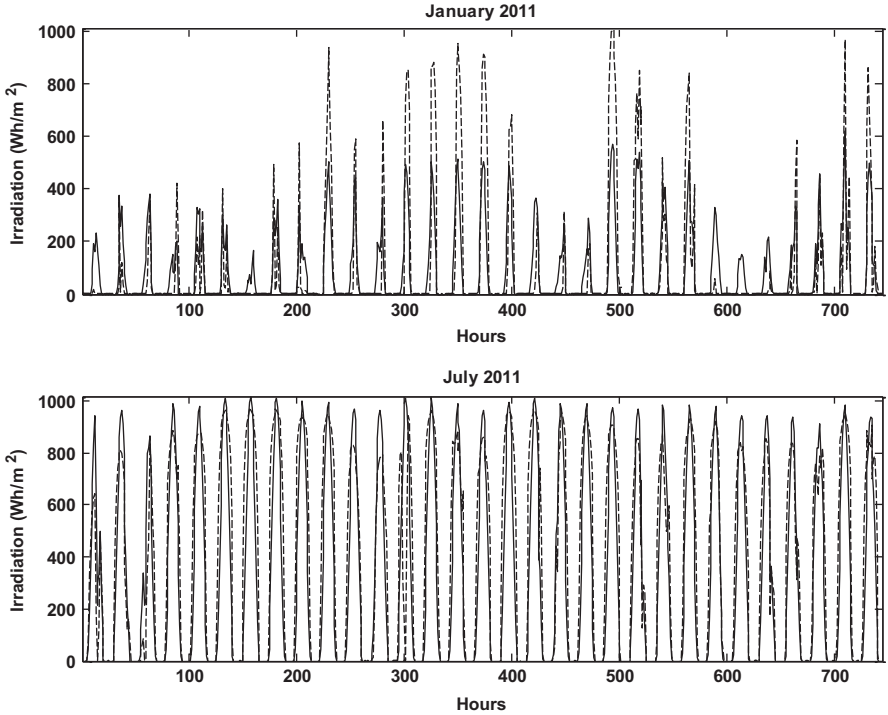


Fig. 1 Hourly solar irradiation (Whm^{-2}) data series corresponding to January 2011 (*upper plot*) and July 2011 (*lower plot*). GHI and DNI are depicted by *solid line* and *dashed line*, respectively

Table 1 Descriptive statistics from January 2009 to December 2011

Month	Mean (Whm^{-2})		Std (Whm^{-2})	
	DNI	GHI	DNI	GHI
Jan	77.58	71.38	209.85	128.58
Feb	163.22	125.55	301.22	195.67
Mar	168.10	165.08	300.90	243.47
Apr	232.22	230.60	331.23	300.37
May	290.35	283.58	351.58	339.38
June	312.43	302.12	356.67	350.35
July	384.28	322.82	382.62	362.30
Aug	317.40	273.33	357.53	330.60
Sept	256.82	209.63	343.40	282.43
Oct	233.67	159.82	339.13	230.73
Nov	133.25	93.82	265.73	159.08
Dec	107.10	72.93	247.38	129.45
Overall	223.03	192.55	315.60	254.37

of making the descriptive statistics related to hourly values of solar radiation easy to read.

3 Models

3.1 Persistence Model and Single Exponential Smoothing

Regarding the problem of solar irradiation forecasting, the most extended technique used to contrast the performance of new models is the persistence model, [20], where the forecast always equals to the last known data point. The persistence model is also known in the forecasting literature as the naïve model or the random walk [21]. Essentially, this model is a particular case of the single exponential smoothing (SES) method [15, 22]. Basically, SES updates the previous forecast by weighting the last forecast error, i.e.:

$$F_{t+1} = F_t + \alpha(y_t - F_t), \quad (1)$$

where α is a constant between 0 and 1. Thus, the persistence model is equivalent to the SES method with $\alpha = 1$.

3.2 Holt–Winters

Typically, time series can be decomposed in different components as trend, seasonality, and irregular term. SES method is adequate when the level is the most important component to explain the time series pattern. Nonetheless, when other typical components as trend or seasonality are present, the previous method should be modified. In the particular case of solar irradiation time series, one of the most important components is the seasonality. Here, the time series has a remarkable periodic behavior every 24 h. A well-known method as the Holt–Winters incorporates those components as follows [21]:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1 - \alpha)[L_{t-1} + b_{t-1}], \quad (2)$$

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1}, \quad (3)$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1 - \gamma)S_{t-s}, \quad (4)$$

$$F_{t+1} = (L_t + b_t)S_{t-s+1}, \quad (5)$$

where s is the seasonality period. We assume a daily seasonality ($s = 24$ h). In order to compute the forecasts one step ahead (F_{t+1}) in (5), we need to know the current

underlying level (2), the current underlying trend (3), and the seasonal index (4). Although the model cannot be interpreted in terms of solar radiation physical phenomena, the proposed technique cannot be considered a pure black box model given that each equation stands for a component of the time series in a statistical meaning. The unknown parameters α , β , and γ are positive constants or smoothing constants that vary between 0 and 1. The aforementioned constants weight the previous estimates with respect to the new observations, and so they do not have a physical interpretation in relation to other models based on geometric effects on solar position. These unknown constants can be estimated by minimizing the sum of the one-step-ahead in-sample forecast errors.

Expressions shown in (2)–(5) are the multiplicative version of the HW method. Nonetheless, it cannot be directly used in our application. The problem is the intermittency of the data, i.e., the solar radiation values of GHI and DNI are zero at night and the algorithm in (2)–(5) may have numerical problems. In order to overcome that issue, we propose the additive HW version in (6), where divisions are replaced by subtractions.

More information about the different expressions that exponential smoothing methods can adopt is available in [23]. Note that the forecasting horizon defined by the constant m is included in the last equation in (6). Since this analysis is limited to short-term forecasting horizons, $m = 1, 2, \dots, 6$.

$$\begin{aligned} L_t &= \alpha(Y_t - S_{t-s}) + (1 - \alpha)[L_{t-1} + b_{t-1}], \\ b_t &= \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1}, \\ S_t &= \gamma(Y_t - L_t) + (1 - \gamma)S_{t-1}, \\ F_{t+m} &= L_t + mb_t + S_{t+m-s}. \end{aligned} \tag{6}$$

Given the recursive nature of the expressions in (6), the first 24 h is required to initialize the algorithm. Typically, the initialization can be achieved as follows:

$$\begin{aligned} L_s &= \frac{(Y_1 + Y_2 + \dots + Y_s)}{s}, \\ b_s &= \frac{1}{s} \left[\frac{(Y_{s+1} - Y_1)}{s} + \frac{(Y_{s+2} - Y_2)}{s} + \dots + \frac{(Y_{s+s} - Y_s)}{s} \right], \\ S_1 &= Y_1 - L_s, S_2 = Y_2 - L_s, \dots, S_s = Y_s - L_s. \end{aligned} \tag{7}$$

4 Experimental Results

In order to test the aforementioned models, a predictive empirical experiment is carried out. The last week of each month (20% of the data approx.) is reserved as a holdout sample, and it is used for evaluating the different forecasting models. The

experiment design proposed here is exhaustive given that models are tested for each month of a whole year rather than testing the models only for a particular month. That is important because the forecast errors are not expected to be constant throughout the year. In this sense, forecast errors of summer months are lower than winter months as a consequence of a stable weather. The forecasting horizon ranges from 1 to 6 h ahead. A rolling origin evaluation experiment is designed as follows. The three previous months with respect to the week to be forecast are reserved as hold-in sample to optimize the coefficients α , β , and γ . For example, the forecast of the last week of January employs the three previous months to optimize the coefficients. Then, with those coefficients, the algorithm in (6) produces the forecast from 1 h to 6 h ahead. Once the forecast is made, the origin is moved 1 h ahead until the last week of January is exhausted. We proceed analogously to forecast the last week of every month for the rest of the year. Note that the estimation of the coefficients α , β , and γ is re-optimized at every hour as the origin is moved. All models have been implemented in MATLAB[®].

The mean absolute error (MAE) is employed to compare the forecasting techniques. The MAE is defined as $\text{MAE} = \text{mean}(|e_t|)$, where e_t is the forecast error given by

$$e_t = (y_t - F_t), \quad t = 1, \dots, T. \quad (8)$$

Here, y_t and F_t stand for the actual value and the forecast, respectively, at time t . Generally, the root mean squared error (RMSE) and the relative root mean squared error (rRMSE) are also used for comparison purposes. The rRMSE is calculated with the following expression:

$$\text{rRMSE} = \frac{\text{RMSE}}{\bar{y}} = \frac{\sqrt{\sum_{t=1}^T (y_t - F_t)^2 / T}}{\bar{y}}, \quad (9)$$

where $\bar{y}$ is the mean of the observed values. Furthermore, Martín et al. [20] define the improvement over persistence as follows:

$$\text{Improvement} = \left(1 - \frac{\text{rRMSE}_m}{\text{rRMSE}_p} \right) \cdot 100, \quad (10)$$

where rRMSE_m and rRMSE_p stand for the relative root mean squared error for the model proposed and the persistence model, respectively.

Table 2 shows the GHI one-step-ahead forecast errors measured by the previously described metrics on the holdout sample. The errors have been broken down depending on the month of the year. In general terms, the proposed model (HW) outperforms the persistence benchmark in every month. It should be highlighted for its good performance on summer given its low value of rRMSE. In fact, during June, July, August, and September, the improvement over the persistence method is greater than 50%. In winter months, particularly for January

Table 2 Different metrics of one-step-ahead forecast errors per month corresponding to the holdout sample of the GHI data

	MAE (Whm ⁻²)		RMSE (Whm ⁻²)		rRMSE		Improv.
	HW	Persis.	HW	Persis.	HW	Persis.	
Jan	40.39	43.71	62.39	77.32	87.40	108.30	19.30
Feb	63.27	83.96	97.39	117.87	77.60	93.90	17.40
Mar	65.95	86.26	98.63	117.76	59.70	71.30	16.20
Apr	91.06	107.33	130.74	149.69	56.70	64.90	12.70
May	99.96	123.90	153.65	164.87	54.20	58.10	6.80
June	16.94	119.43	23.47	136.06	7.80	45.00	82.80
July	31.71	121.08	59.28	142.45	18.40	44.10	58.40
Aug	33.68	118.23	58.16	137.14	21.30	50.20	57.60
Sept	31.33	113.13	45.33	132.80	21.60	63.30	65.90
Oct	58.47	77.11	97.60	110.13	61.10	68.90	11.40
Nov	28.13	58.86	45.86	83.75	48.90	89.30	45.20
Dec	13.19	50.78	20.86	76.12	28.60	104.40	72.60
Overall	47.84	91.98	74.45	120.50	45.30	71.80	38.80

and February, the rRMSE is relatively high. This is due to two reasons: (1) higher climate instability and ii) the percentage nature of the error metric provides high values when the solar radiation on average is low, as it is expected in winter months. The last row in Table 2 shows the overall performance of the HW and persistence models along the whole year. In summary, the HW yields an improvement ratio of 38.8% over the persistence model. Units in Table 2 have been represented in terms of the solar energy per area (Whm⁻²) for the purpose of making the descriptive statistics related to hourly values of solar radiation easy to read.

Analogously, Table 3 shows the DNI one-step-ahead forecast errors on the holdout sample. In general terms, the same conclusions previously found still hold. However, the improvement extent achieved is lower with respect to the GHI results because of the higher data volatility. Again, the overall performance of the HW method is shown in the last row of Table 3. In summary, the HW reduces on average up to 20.8% of the forecast errors provided by the persistence model.

In order to find out whether the HW forecasting accuracy is competitive, a comparison of errors found in the literature should be provided. In that sense, Kraas and collaborators in [2], reviewed the forecasting errors achieved by different techniques in different locations for the variables GHI and DNI. In summary, the rRMSE for GHI forecast was found to be in the range of 30–50%. Meanwhile, the results for the DNI were about 56–77%. If we compare those numbers with the overall rRMSE of the HW, we can corroborate the correct performance of the HW. It should be remarked that, whereas those techniques rely on complex and expensive models, the HW can be implemented straightforwardly in a spreadsheet.

Some examples of the forecasts achieved are shown in Figs. 2 and 3. Figure 2 depicts the one-step-ahead forecasts for the last week of June 2011. Actual values are depicted in a solid line and forecasts are in a dashed line. The upper panel shows

Table 3 Different metrics of one-step-ahead forecast errors per month corresponding to the holdout sample of the DNI data

	MAE (Whm ⁻²)		RMSE (Whm ⁻²)		rRMSE		Improv.
	HW	Persis.	HW	Persis.	HW	Persis.	
Jan	72.69	62.50	140.42	147.46	181.00	190.10	4.80
Feb	99.66	122.18	166.67	207.30	102.10	127.00	19.60
Mar	103.47	101.85	163.55	174.57	97.30	103.80	6.30
Apr	113.46	116.91	164.79	187.06	71.00	80.60	11.90
May	128.86	131.66	178.55	189.58	61.50	65.30	5.80
June	53.84	103.68	80.76	145.24	25.80	46.50	44.40
July	74.82	122.34	109.21	170.10	28.40	44.30	35.80
Aug	81.08	118.36	105.46	167.26	33.20	52.70	36.90
Sept	86.83	145.03	131.91	193.51	51.40	75.30	31.80
Oct	102.07	117.69	179.12	190.08	76.70	81.30	5.80
Nov	104.67	107.56	162.26	184.55	121.80	138.50	12.10
Dec	71.75	96.54	114.50	175.53	106.90	163.90	34.80
Overall	91.10	112.19	141.43	177.69	79.80	97.40	20.80

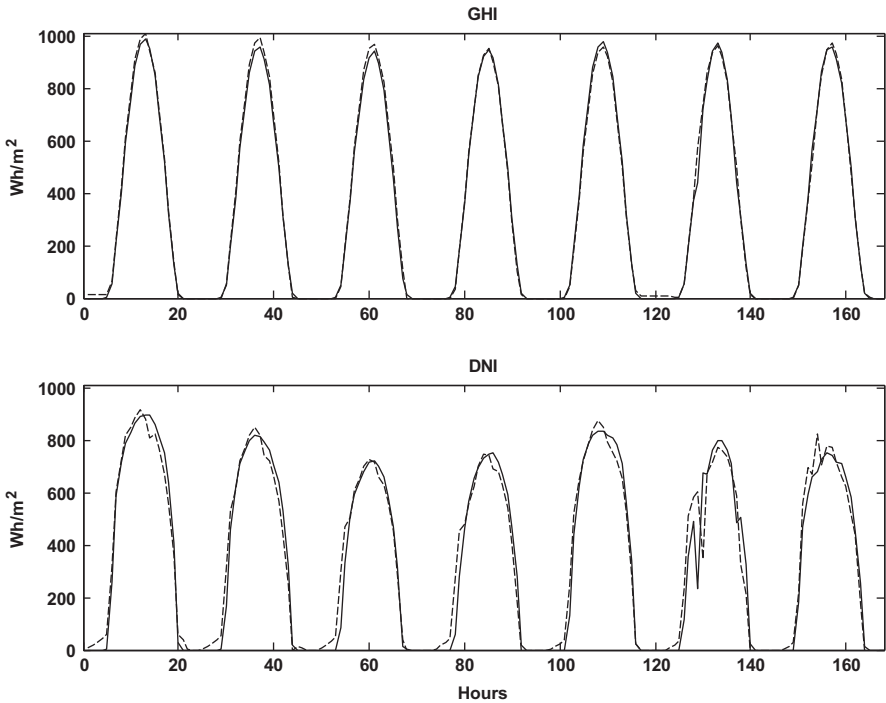


Fig. 2 One-step-ahead hourly forecasts during the last week in June 2011. Actual and forecast values are depicted by *solid* and *dashed* line, respectively. *Upper plot* shows GHI forecasts. *Lower plot* shows DNI forecasts

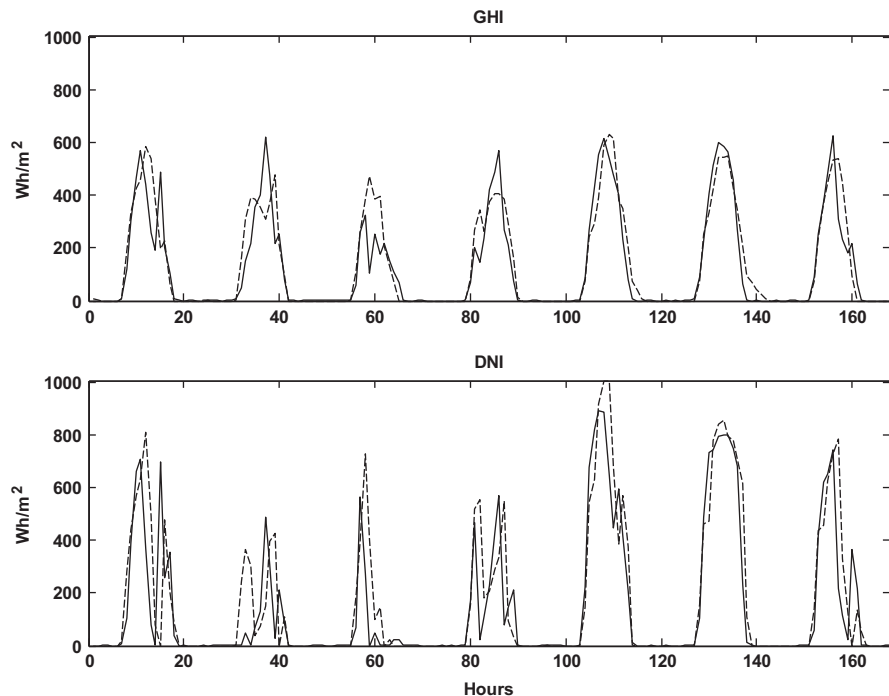


Fig. 3 One-step-ahead hourly forecasts during the last week in October 2011. Actual and forecast values are depicted by *solid* and *dashed* line, respectively. *Upper plot* shows GHI forecasts. *Lower plot* shows DNI forecasts

the results for the GHI variable, whereas the DNI variable is shown in the lower panel. The figures show how the HW method is capable of capturing the clear seasonality of the data and to provide reasonable forecasts. It is also visible how the variable DNI is more difficult to forecast, and the differences between actual and forecasted values are more apparent.

Summers in this area of Spain are typically rather stable, and it makes sense that solar radiation during these days is more feasible to forecast.

Nonetheless, months that belong to spring or autumn are more variable. In order to show the HW performance for those months, Figure 3 shows the results achieved during the last week in October 2011. Again, the solid line represents the actual values and the dashed line the forecasts. Here the forecasts are not as precise as the previous figure, but still they provide competitive forecasts. It should be noted that, although both GHI and DNI depend on cloud cover conditions, DNI is more sensitive than GHI to atmosphere changes as turbidity conditions (atmosphere composition due to the aerosol content and other particulates in the air) and this makes DNI more difficult to forecast, and thus, its forecast errors are also higher than the GHI ones. Note that this discrepancy between forecasting accuracy is in accordance with the literature [2].

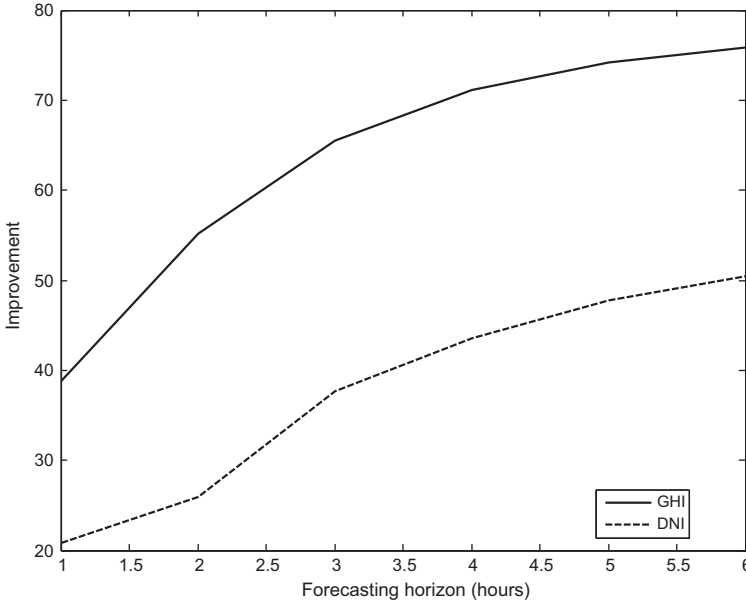


Fig. 4 Improvement of HW on persistence model in the holdout sample vs. forecasting horizon. GHI and DNI are depicted by *solid* and *dashed* line, respectively

So far, the forecasting performance of the proposed models for one-step-ahead forecasting horizon has been analyzed. Figure 4 shows the evolution of the improvement metric with regard to broader forecasting horizons. Since this study is devoted to short-term horizons, the longest horizon is set to 6 h. This picture shows how the improvement of the HW with respect to the persistence raises with the forecasting horizon in a nonlinear fashion. This improvement increase is due to the HW model's capability to capture the seasonality of the data, unlike the persistence model. In addition, the lower improvement ratios achieved by the DNI remark again the difficulties of forecasting the solar radiation measured by DNI instead of GHI.

5 Conclusions

In order to efficiently incorporate renewable energies into the grid, it is very important to provide accurate forecasts. In the particular case of solar energy, the key variable is solar radiation. In recent years, novel methodologies have proliferated to forecast solar radiation with different complexity levels. Nonetheless, there is not unanimity about which technique is the most adequate. In certain extent, this is due to the difficulties found to reproduce the results given the geographical dispersion of each experiment. Nevertheless, another potential reason might be the lack of appropriate benchmarks. Typically, the persistence model is used to test new models.

This article analyzes the Holt–Winters exponential smoothing performance to tackle the problem of solar radiation forecasting. This exponential smoothing version is easy to implement that relaxes the necessity of statistical experts or expensive software. For those reasons, this technique is broadly employed in industry for demand forecasting applications.

The results show that the Holt–Winters method improves significantly the forecast accuracy with regard to the persistence model and it can be considered as a competitive forecasting technique. These conclusions have been validated on the basis of GHI and DNI data measured in weather stations located in Spain. Given the univariate nature of the Holt–Winters that uses only past information to provide forecasts, it seems probable that other techniques that incorporate exogenous variables could improve the Holt–Winters results. In any case, the Holt–Winters approach would be a hard to beat benchmark.

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