Solar Power Time Series Prediction Using Wavelet Analysis

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Abstract- Following the major revolution in the sun energy field, the forecast of this one is getting increasingly relevant in competitive electricity markets. Since the solar energy produced is acutely dependent on the weather conditions, the unanticipated variation in the solar power would increase operating cost. Furthermore, the unpredictability of the output power will be a significant hindrance in incorporating this variable energy resource into the network. The object of this paper is to afford an accurate solar power forecasting technique, that may reduce the inaccuracies involved with predicting the near future generation at different weather conditions. This technique is based on the association of the wavelet transform (WT) with ANN and SARIMA models. In this proposed model the WT is used to ensure a considerable effect on the ill-behaved solar power time-series. The ANN and the SARIMA models are applied to both approximation and detail components of the WT in order to capture the nonlinear behavior of the solar power data. The second aim of this study is to evaluate the impact of the detail components of the WT, by comparing the predicted outcomes with and without the detailed elements. The reliability of the suggested models has been demonstrated by comparing statistical performance measures in terms of MAPE and RMSE.

Keywords- solar power, renewable energy, time series, wavelet transform, artificial intelligence, ANN, SARIMA.

1. Introduction

The world has become industrialized and energy needs are rising rapidly in terms of comfort and consumption to sustain both financial growth and individual's needs. Currently, the main sources of energy are conventional fossils and fuels, which combine two important negative aspects: they are present on earth in limited quantities and emit greenhouse gases [1]. The benefit of renewable energy sources is its availability in unlimited quantities and it has the ability to provide electricity during grid outages due to extreme weather or other emergency circumstances by greatly improving the resilience of the electricity grid. Unfortunately, most of these renewable sources of electricity are intermittent [2]. For this reason, the integration of RE into electricity networks is an important issue. However, in order to take advantage of this capability, RE systems must be built with resiliency in mind and coupled with other technology, such as energy storage, auxiliary generation and prediction technique of the different resources [3]. Increasing the resilience of the grid can reduce the time and resources needed to supply power to critical facilities. Deployment of solar power technologies in combination with the prediction technique allows solar power to contribute to the resilience of the grid by supplying localized power when the grid is down.

Predicting power output of solar systems is a difficult mission because it relies extremely on exogenous factors such as solar radiation and climate particularities. The photovoltaic power prediction approaches are classified primarily into three sets of groups: physical, statistical and machine learning models. The physical model depends principally on the correlation between the rules of physics and the sun radiation [4] and it includes: numerical weather prediction [5], total sky image [6] and satellite image [7]. The statistical models focus mainly on historical data in order to forecast future time series, moreover, they are five sub-models that are used in the statistical model such as fuzzy theory [8], grey theory [9], Markov chain [10], autoregressive [11] and regression model [12]. The autoregressive moving average models are a stochastic model that is based on probability theory, they can reflect time variation in the data [13]. Moreover, there are several types of autoregressive models, such as periodic autoregressive moving average model [14], autoregressive moving average models with the auxiliary inputs [15], autoregressive integrated moving average model [16] and the seasonal autoregressive integrated moving average model [17], which allow the researchers to create synthetic time series taking into account cyclical fluctuations in the observed records. These models are widely used in solar and weather forecasting [18, 19]. However, the application of machine learning and deep learning methodologies to forecast photovoltaic power has gained attention within the scientific and industrial communities over the last ten years [20]. For instance, the Machine learning model has the ability to deal with complex problems [21]. It contains: support vector machine [22], decision tree [23], and artificial neural network [24] that is one of the most commonly utilized techniques for predicting time series [25, 26].

Compared with traditional approaches, Almonacid. F [27] has used artificial neural network to predict the annual energy produced by a PV generator. The results showed that this model achieved better performance than the traditional approaches since this method considers certain second-order effects, for instance: angular and spectral effects.

To forecast intermittent demand Lolli. F [28] has proposed a single-hidden layer feed-forward neural network. Its model can be implemented easily, however, the forecasting accuracy is not as high as back-propagation algorithm, while the study mentioned above has provided optimal results. In this case, only one hidden layer was chosen since the data features cannot be completely extracted. The reason why only one hidden layer is chosen is the specificity of the training algorithm, too many hidden layers can make difficult to train the neural network, furthermore, it is susceptible to issues including over-fitting, falling into local minimum value and the gradient disappearance [29].

Over a decade, people have been conducting researches until the Deep Network was established in 2006 [30]. Gradually, deep networks are developed, as a consequence, the difficulties in training and gradient disappearance are alleviated. With the ongoing development of computer hardware, many researchers have been devoted attention to the big data technology and the deep learning networks. So far, various deep neural network models have been proposed such as back propagation neural network [31], convolutional neural network [32], deep network [33], long short-term memory neural network [34], generative adversarial network [35], deep residual network [36] and more. Most time series don't possess a strictly linear or non-linear association between their values. Thus, it is hard to define their linearity or non-linearity. The combination of statistical methods and artificial neural network models can therefore lead to an appropriate prediction.

Wang. K [37] has proposed a hybrid model associating autoregressive integrated moving average with a neural network, his study has demonstrated that developing hybrid model is an efficient technique for fitting the linear and nonlinear time-series data patterns.

Gairaa.K [38] has introduced a new hybrid model incorporating the linear autoregressive moving average model and the nonlinear artificial neural network model, his research has demonstrated that the hybrid model has been improved in terms of the mean absolute error of 18.1% and 2.7% compared to ARMA and ANN.

Nowadays, the prediction of solar radiation becomes complicated with the continuous growth of microgrid, the single method of prediction is difficult to fulfil the need for the prediction of solar energy. Therefore, researchers have begun to build a hybrid prediction approaches in light of several existing approaches coupled with multiple decomposition algorithms, Specifically, wavelet decomposition (WD) [39]. This hybrid approach mainly combines WT with ARIMA [40], WT with artificial neural network [41], WT with Neuro fuzzy approach [42] and more.

Hussain. S [43] has presented a hybrid technique to improve the performance of a multilayer perceptron (ANN) model using wavelet transform to break down the complex meteorological signals into relatively simple components, the results prove that the suggested strategy enhances significantly the efficiency of the ANN model with a maximum improvement of 6.84% in R^2.

Eseye. T [44] has proposed a hybrid predicting model incorporating wavelet transform, particle swarm optimization and support vector machine. In this configuration, the wavelet transform is utilized to obtain a major effect on improper data. The forecasting results of the proposed model show a significant growth in accuracy comparing with other models.

This paper contributes to provide a comparison between new two hybrid models of solar power forecasting namely WT-SARIMA-ANN. The original time series is divided into estimated and detailed parts through the implementation of wavelet decomposition. The second purpose of this work is to assess the impact of the detail components of the WT, by comparing the predicted outcomes with and without the detailed elements of the time series. In addition, all the outcomes of the predictions obtained were compared with the persistence reference model for a proper benchmark test. As a result, the hybrid WT-ANN and WT-SARIMA prediction models developed show high performance in the daily photovoltaic power forecasting.

This work is structured in 5 parts: the part 2 defines WT, ANN, and SARIMA. The part 3 describes the suggested model. The part 4 explains the result of the comparison. Lastly, part 5 presents the conclusion

2. Description of Wavelet Transform, ANN and SARIMA

This section offers mathematical formulas for models used to forecast daily solar power and to analyze errors.

2.1 Wavelet Transform

The time series of the solar radiation includes numerous fluctuations, spikes, and different non-stationarities forms. The WT can be considered as a filtering method for isolating such spikes. As a consequence, this transformation can be used to minimize the forecasting error and promote prediction [45]. The WT formula is divided into continuous (CWT) and discrete (DWT).

The CWT is defined as [46]:

$$CWT_y(c,d) = \frac{1}{\sqrt{|c|}} \int_{-\infty}^{+\infty} \Psi^*(t)\, y(t) dt \tag{1}$$

$$\Psi_{(c,d)}(t) = \frac{1}{\sqrt{|c|}} \Psi\left(\frac{t-d}{c}\right) \tag{2}$$

Where y(t) is the analyzed signal, $\Psi_{(c,d)}(t)$ is the mother wavelet scales by a factor (c) and shifted by a translated parameter (d), The low frequencies extend the signal and provide non-detailed signal information, meanwhile, the high frequencies contract the signal and generate detailed signal information.

The DWT is giving by [46]:

$$DWT_y(p,q) = 2^{\frac{-p}{2}} \sum_{t=0}^{T-1} y(t) \Psi(\frac{t-q.2^p}{2^p}) \tag{3}$$

Where T is the signal y(t) length, the scaling and translation parameters are the functions of the integer variables p and q, where, $c = 2^p$ and $d = q.2^p$, t is the discrete time variable.

For a three-level decomposition of the solar power series, the signal y(t) is split into a number of constituent elements. The approximation cA3(t) reflects the general trend and provides a smooth signal shape. The terms cD1,2,3(t) depicts the high-frequency elements in the signal, which carries detailed information.

An illustration of the three levels transformation is given in figure 1.

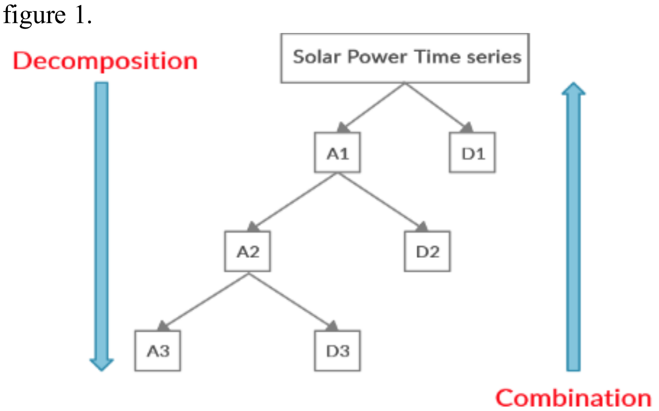

Fig. 1. Multilevel decomposition of solar power timeseries

In this study, Daubechies 3 is utilized as a wavelet function [47]. In general, there are two components in a typical solar power series: the trend component and the detailed information [45]. As shown in Figure 2, cA3 shows a general pattern close to the historic solar power series, which has a clear annual periodicity. cD3 has a comparable annual periodicity. Moreover, cD1 and cD2 incorporate chaotic detailed information without any regularity.

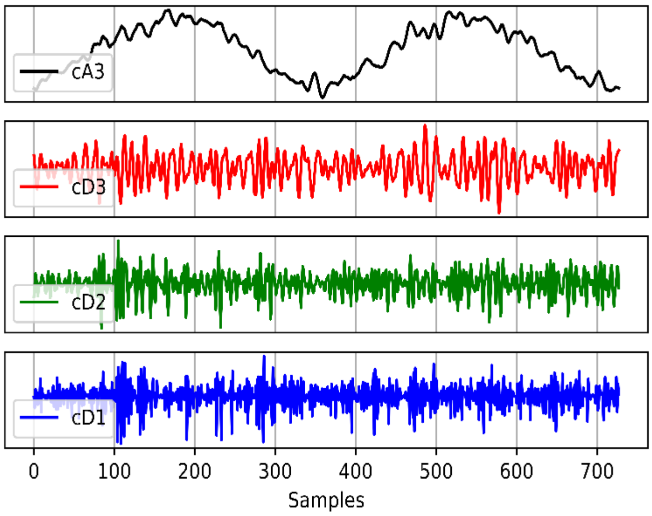

Fig. 2. Decomposed wavelet solar power series of the historical data

2.2 Artificial neural network

The Artificial neural networks have been employed in power systems to deal with various problems [48, 49]. ANNs are favored because they can imitate natural intelligence by learning from past experiences [50]. This type of artificial intelligence technique consisting of basic processing sections named neurons that functioned as the brain of a human being [51]. ANNs have, also the ability to model linear and nonlinear systems.

The mathematical expression used to estimate daily solar power by applying neural networks can be expressed as below [52]:

$$T_j = f\left(O_j - b_j\right) \tag{4}$$

$$O_j = \sum a_{ji}\, p_i \;\; \forall i = 1,2,\ldots\ldots,r \tag{5}$$

Where T_j is the output of the hidden layer, $f(\,)$ is the activation function, b_j is the bias value, r is the number of input signals, p_i is the input signal and a_{ji} is the weights between the neuron i in the input/hidden layer to neuron j in hidden/output layers.

ANNs are designed in order that a distinct input drive to a specific target output. The discrepancy between output and target is employed as an update law for artificial neural network before the output hits the target. In this paper, the number of the hidden layers is determined by one-step ahead forecasting Root Mean Squared Error (RMSE) (Fig.3).

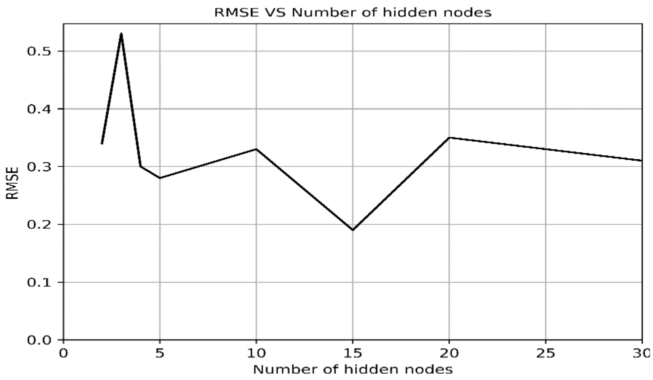

Fig. 3. RMSE versus the number of hidden layers

2.3 Seasonal Autoregressive Integrated Moving Average

SARIMA models are suitable for seasonal time series modeling, in which the mean and other statistics are not stationary over the year for a given season [53]. It is a kind of short-term prediction model in time series analysis [54].

The general expression of the SARIMA model is defined as follows [55]:

$$\phi_p(B^m)\varphi(B)\nabla_m^D\nabla^d X_t = \Theta_Q(B^m)\theta(B) \qquad (6)$$

Where, W_t presents the nonstationary, m indicates the period of the time series. $\varphi(B)$ and $\theta(B)$ of order p and q are polynomials present the ordinary AR and MA elements. $\phi_p(B^m)$ and $\Theta_Q(B^m)$ are the seasonal autoregressive and moving average components, where P and Q present their orders. ∇^d and ∇_m^D are ordinary and seasonal difference elements. B indicates the backshift operator [56].

The expressions of the different components are given by [56]:

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p \qquad (7)$$

$$\phi_P(B^m) = 1 - \phi_1 B^m - \phi_2 B^{2m} - \cdots - \phi_p B^{pm} \qquad (8)$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \qquad (9)$$

$$\Theta_Q(B^m) = 1 + \Theta_1 B^m + \Theta_2 B^{2m} +..+\Theta_Q B^{Qm} \qquad (10)$$

$$\nabla^d = (1 - B)^d \qquad (11)$$

$$\nabla_m^D = (1 - B^m)^D \qquad (12)$$

$$B^k X_t = X_{t-k} \qquad (13)$$

2.4 Performance Assessment

The absolute percentage error (MAPE) and the root mean square error (RMSE) are calculated, in order to evaluate the efficiency of the previously-mentioned forecast models.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_i^f - X_i^a|}{\overline{|X_i^a|}} \qquad (14)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_i^f - X_i^a\right)^2} \qquad (15)$$

Where N indicates the total number of information points; X_i^f presents the predicted solar power information X_i^a specifies the veritable solar power information, and $\overline{|X_i^a|}$ is an average of the actual solar power data.

3. Proposed Model

The structure of the suggested hybrid WT-ANN-SARIMA model is discussed in this section. As illustrated in Figure 4.

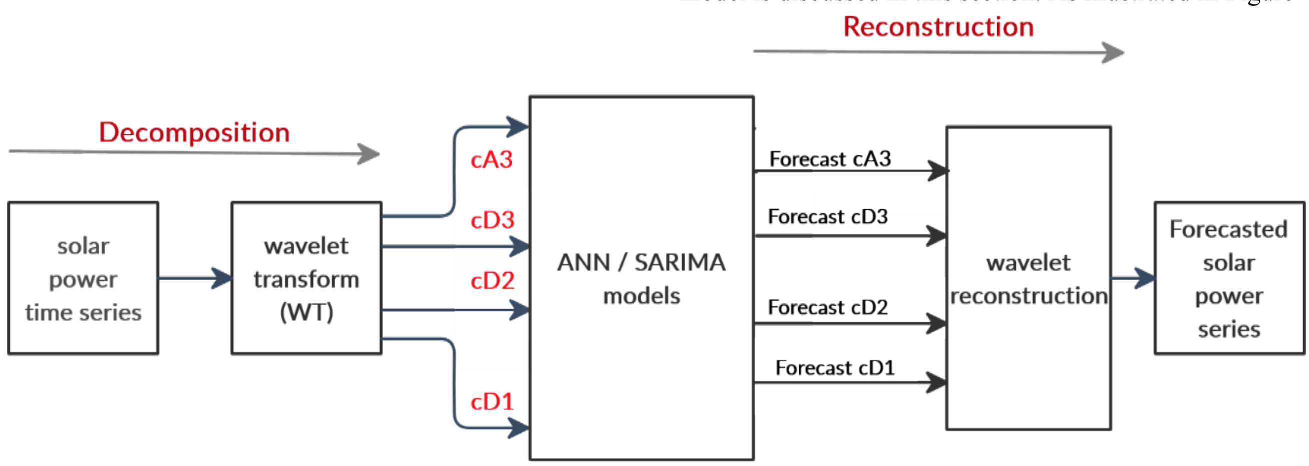

Fig. 4. The architecture of the proposed structure

The detailed structure is described as follows:

A. The original solar power series is divided by the WT into one periodical and three detailed solar power series respectively. The decomposed series are assembled into training and testing period.

B. For the SARIMA model, the lags of the approximation and detailed elements are determined by the Akaike Information Criterion. For the neural network, the number of hidden nodes is determined by one-step ahead forecasting Root Mean Squared Error (RMSE) for every decomposed subseries.

C. ANN with WT are employed to estimate the approximation without using detailed elements. This implies that the detailed components are just noise.

D. SARIMA with WT are employed to estimate the approximation without using detailed elements. This is the same as C.

E. ANN and SARIMA are applied to both approximation and detailed components. In this case, detailed components are used, which indicates that these components are essential variables to pick up the volatility of the primitive series. The numbers of detail components used in the forecasting models range between one and three. In other words, we are creating 3 separate forecasting models: the first model with just one detail component, the second model with two, and a third model with three detail components.

The three cases mentioned above are studied in order to compare the forecasting results. Otherwise, the above three cases are performed to illustrate the overestimation effect. The other goal is to illustrate the results of the incorporation of detailed components in the forecasting models. At this point, the detailed components are considered to be a random process with heteroskedasticity and mean zero. The basis of this statement is the results of [57, 58], And it's very reasonable to conclude that, when we see the volatility of the detailed components, the results obtained are intended to recognize the detailed components impact.

F. Reconstruction of the predicted series and comparison of the results: if the detailed components of the solar power series will reflect a dispensable noise, or a critical ingredient for enhancing the performance of the prediction.

4. Results and Discussion

Using the (ANN) and the (SARIMA) models with WT, the future solar power is estimated from the historical solar power timeseries. The MAPE and the RMSE are used as output evaluators for the proposed strategy. In this study, 80% of global data is used to fit the models and the rest is used for evaluating purposes. Furthermore, the performance of the developed hybrid wavelet-ANN and wavelet-SARIMA prediction models were compared with the persistence reference model (Zero-Rule algorithm). As it is shown in figure 5 The performance of the persistence reference model in the daily solar power forecasting was found as 1.027 for the root mean square error (RMSE) and 27.7% for the mean absolute percent error (MAPE).

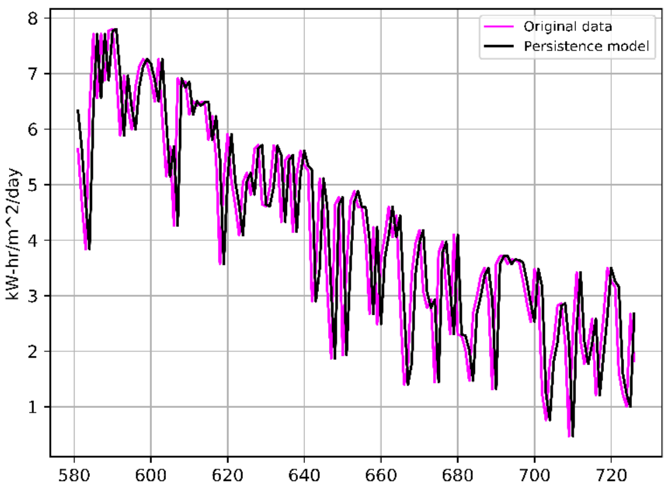

Fig.5. The predicted solar power values of the persistence model versus the original value

The daily solar power prediction results for the Wavelet SARIMA model are presented in Table 1. In case of examining the error values in this table, RMSE of 0.82 and MAPE of 31% were found for cA3 input. RMSE of 0.69 and MAPE of 25.5% were found for cA3 and cD3 inputs. RMSE of 0,52 and MAPE of 17% were found for cA3, cD3, cD2 inputs. RMSE of 0.29 and MAPE of 11% were found for cA3, cD3, cD2 and cD1 inputs. The best prediction output was obtained by the WT-SARIMA model, which used cA3, cD3, cD2 and cD1 as inputs.

Figure 6 shows the expected solar power values using WT-SARIMA hybrid model, with and without the detailed components. As it is shown, it is obvious that a good match between the forecasted and measured values is happening when all the detailed series are used. On the other hand, the WT-SARIMA model, which used cA3 input, with RMSE of 0.82 and MAPE of 31%, caused the worst prediction results. Compared to the persistence reference model the accuracy of the prediction was improved by 71.76% for the WT-SARIMA model.

Table 1. Daily solar power prediction results of the Wavelet-SARIMA model

No	Model	Inputs	MAPE	RMSE
1	WT+ SARIMA	cA3	31%	0.82
2		cA3+cD3	25.5%	0.69
3		cA3+cD3+cD2	17%	0.52
4		**cA3+cD3+cD2 +cD1**	**11%**	**0.29**

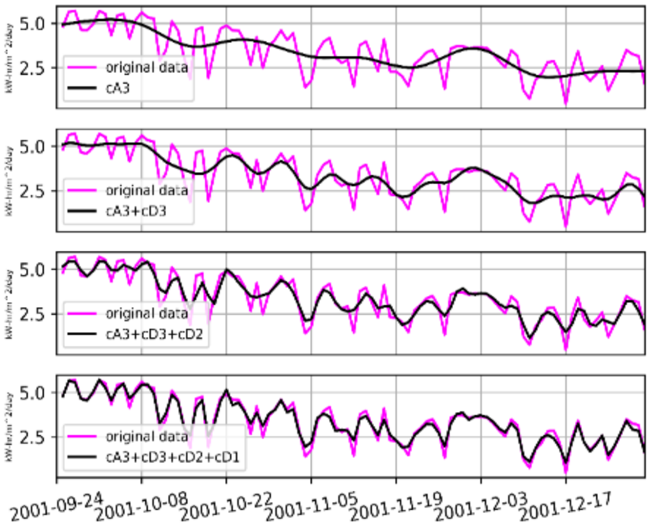

Fig.6. Forecasting result of WT-SARIMA model with and without noisy wavelet decomposition

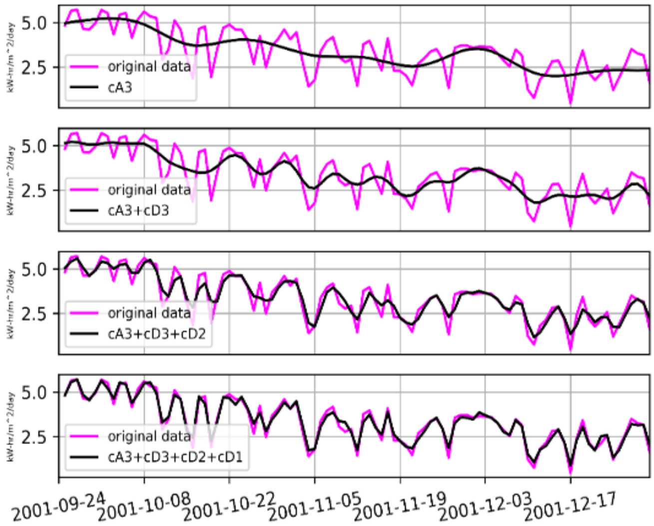

Fig.7. Forecasting result of WT-ANN model with and without noisy wavelet decomposition

The daily solar power forecast results for the Wavelet-ANN model is illustrated in Table 2. In case of investigating the error values in table 2, RMSE of 0.82 and MAPE of 28% were found for cA3 input. RMSE of 0.69 and MAPE of 24% were found for cA3 and cD3 inputs. RMSE of 0,45 and MAPE of 15% were found for cA3, cD3, cD2 inputs. RMSE of 0.24 and MAPE of 8% were found for cA3, cD3, cD2 and cD1 input. The best forecast performance was obtained from the WT-ANN model, which used cA3, cD3, cD2 and cD1 as inputs. Figure 7 displays the expected solar power values using the WT-ANN hybrid model, with and without the detailed components. On the other hand, the WT-ANN model, which used the cA3 input, with an RMSE of 0.82 and a MAPE of 28%, provided the worst prediction results. Compared to the persistence reference model the accuracy of the prediction was improved by 76.63% for the WT-ANN model.

Table 2. Daily solar power prediction results of the Wavelet-ANN model

No	Model	Inputs	MAPE	RMSE
1	WT+ ANN	cA3	28%	0.82
2		cA3+cD3	24%	0.69
3		cA3+cD3+cD2	15%	0.45
4		**cA3+cD3+cD2 +cD1**	**8%**	**0.24**

The scatter plots of the estimated solar power using WT-SARIMA and WT-ANN models against the measured values during the testing period, under different combinations of detailed series are represented respectively in figures 8 and 9. As shown in theses figures, the plotted data points, in the case of using three detailed series, generally correlated closer towards the fitting line compared with other proposed cases. The figures also illustrate that more the detailed components of the WT are added as an input of the forecasting models, more the difference between the actual outcomes and generated forecasts decreases for both WT-ANN and WT-SARIMA models.

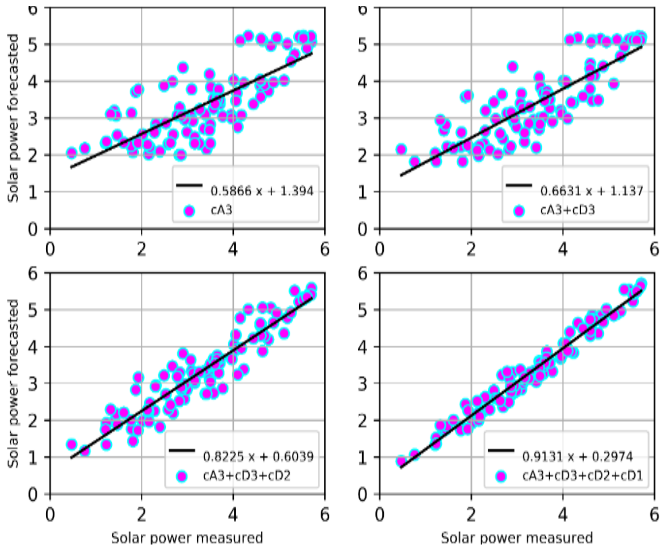

Fig.8. Scatter plot of predicted outcomes of the SARIMA model with and without detailed components versus the original data

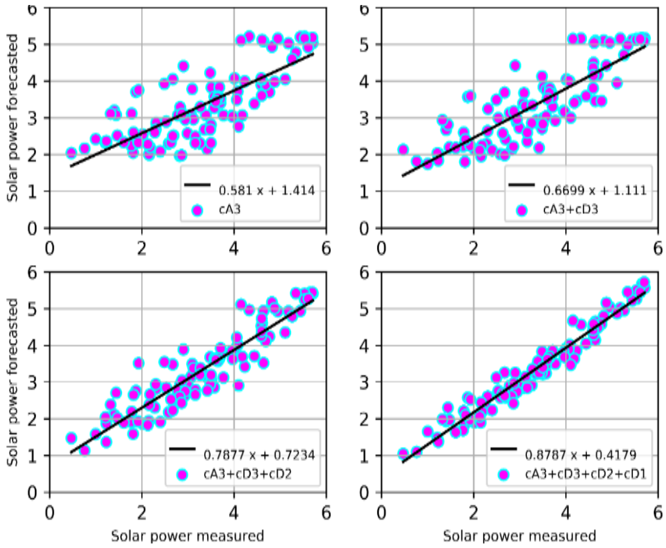

Fig.9. Scatter plot of predicted outcomes of the ANN model with and without detailed components versus the original data

In this work, the proposed models are trained with series resulting from WT. The solar power is forecasted by applying numerous combinations of approximation / detailed series and, their statistical errors are assessed. To test the validity of the proposed strategy on different weather conditions the proposed study was extended for additional countries that are characterized by different weather particularities. For instance: Jakarta/Indonesia, Johannesburg/South Africa and Texas/USA. The values of the statistical errors obtained from different combinations at different weather conditions, illustrate that the proposed approach for estimating the daily solar power is successfully implemented for different weather conditions and, it perfectly estimates the daily solar power with a very low error (RMSE, MAPE) at different climatic particularities when the three detailed series are used with ANN or SARIMA models. The RMSE values derived from different combinations at different weather condition are listed in figure 10.

Case 1: Rabat/Morocco

WT+SARIMA: without detailed components the MAPE and the RMSE values are 31%, 0.82 respectively, and decrease to 11%, 0.29 respectively when three details components are included.

WT+ANN: without detailed components the MAPE and the RMSE values are 28%, 0.82 respectively, and decrease to 8%, 0.24 respectively when three details components are included.

Case 2: Jakarta/Indonesia

WT+SARIMA: without detailed components the MAPE and the RMSE values are 6%, 0.378 respectively, and decrease to 1.4%, 0.132 respectively when three details components are included.

WT+ANN: without detailed components the MAPE and the RMSE values are 4.6%, 0.383 respectively, and decrease to 1.5%, 0.144 respectively when three details components are included.

Case 3: Johannesburg/South Africa

WT+SARIMA: without detailed components the MAPE and the RMSE values are 4.7%, 0.5 respectively, and decrease to 1.4%, 0.15 respectively when three details components are included.

WT+ANN: without detailed components the MAPE and the RMSE values are 4.7%, 0.5 respectively, and decrease to 1.8%, 0.205 respectively when three details components are included.

Case 4: Texas/USA

WT+SARIMA: without detailed components the MAPE and the RMSE values are 2.5%, 0.15 respectively, and decrease to 0.8%, 0.05 respectively when three details components are included.

WT+ANN: without detailed components the MAPE and the RMSE values are 2.5%, 0.15 respectively, and decrease to 0.9%, 0.056 respectively when three details components are included.

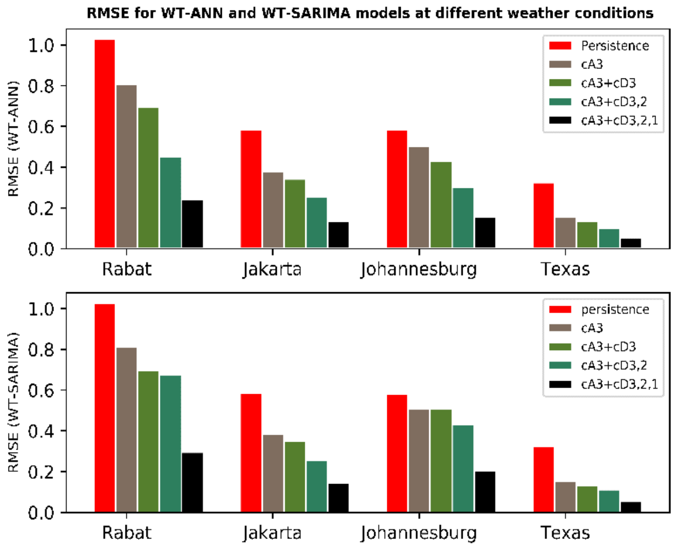

Fig.10. RMSE for WT-SARIMA and WT-ANN at different weather conditions

5. Conclusion

This paper exhibits a comparison between different configuration of hybrid approaches to forecast solar power time series. The suggested approach is founded on the association of WT with SARIMA and ANN. The stochastic behavior of the solar power time series is filtered through WT. Furthermore, the SARIMA and ANN models significantly capture the nonlinear solar power fluctuations. In conclusion, the WT-ANN and WT-SARIMA models are equivalent in terms of prediction quality with a slight advantage of WT-ANN. The prediction accuracy was highly improved according to the persistence reference model. Our study demonstrates that the introduction of detailed components increases the quality of prediction at different weather particularities. This is proved by the value of the MAPE which starts from 31% (without detail components) and decreases to 11% when three detailed components are added in the region of Rabat/Morocco (WT-SARIMA case). And starts from 28% (without detail components) then decreases to 8% when three detailed components are added in the same area (the WT-ANN case). The exposed work is elaborated to mitigate an essential issue of solar power prediction. As the results show, the association of the WT with SARIMA and ANN increases the accuracy and the efficiency of the prediction.

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