Forecasting Hourly Solar Radiation using a Novel Hybrid Technique based on Machine Learning Models

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Abstract: Photovoltaic production is highly dependent on solar radiation time series, which is sporadic. Grid operators have a significant problem integrating photovoltaic energy sources into the electrical grid due to the unpredictability of solar radiation. To overcome this, forecasting global solar radiation can solve the intermittency due to the variability of weather conditions. It allows the grid operators to predict photovoltaic power production to facilitate the planning and dispatching tasks of the electric grid. In this work, we have proposed a new hybrid method to predict one-hour solar radiation in Évora city (Portugal). The hybrid model is based on the daily classification of global solar radiation and machine learning algorithms such as support vector machines (SVM) and artificial neural network (ANN). We have collected five years of global horizontal solar radiation data from the meteorological station of Évora city. We have evaluated the performance of the proposed model using normalized root mean square error (nRMSE) and normalized mean absolute error (nMAE). The results show that, for sunny days, the SVM model performs better than the ANN model with nRMSE = 9.15 % and nMAE = 4.65%, while for cloudy days, the ANN model gives better results than the SVM model with nRMSE= 42.09 % and nMAE = 25.1%. Moreover, we have carried out a performance comparison with the recent literature. The results show the superiority of the proposed hybrid model compared to literature's models.

1 INTRODUCTION

The integration of photovoltaic energy into the electric grid makes its management difficult due to the variability of this renewable energy source. To overcome this, the forecasting of photovoltaic production can facilitate the task of planning and scheduling the operations of the electric grid with the existence of photovoltaic energy sources. The main meteorological parameter that defines photovoltaic production is solar radiation (Mellit, 2010). Consequently, the forecasting of solar radiation allows easy prediction of photovoltaic production. Researchers have proposed various models for this purpose, which may be divided into three groups. The first group includes models based on numerical weather prediction (NWP), which solve the physical equations of the atmosphere to provide short- and medium-term forecasts. (Mathiesen, 2011; Voyant, 2017). The second group consists of models based on sky images and satellite images (Perez, 2010; Yang, 2014). The approaches based on sky images are used for very short-term prediction (Voyant, 2017), while the techniques based on satellite images are widely

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utilized to generate short-term forecasts (Yagli, 2019). The third group represents machine learning (ML) models that aim to learn the relationship between inputs and outputs from meteorological data. These ML models are used for very short-term and short-term forecasting.

Recent studies on solar radiation forecasting have paid attention to ML models because of their high performance (Voyant, 2017; Yagli, 2019). (Benali, 2019) found that random forest (RF) is the best model for forecasting hourly solar radiation in Algeria. (Belaid, 2020) proposes support vector machines (SVM) for predicting the next hour of solar radiation. The outcomes show the superiority of the proposed SVM approach compared to the literature's methods. (Aljanad, 2021) developed a hybrid artificial neural network (ANN) model using the particle swarm optimization (PSO) algorithm for predicting global solar irradiance in Malaysia. The findings demonstrated the effectiveness of the hybrid approach for very short term intervals. (Marzouk, 2020) used an evolutionary algorithm to optimize the ANN model for solar radiation prediction for up to six hours. The results show that the proposed hybrid approach outperforms several models such as smart persistence, regression tree and RF. In reality, comparing the performance of all these techniques described above appears challenging because each model has its dataset, its prediction horizon, and its evaluation criteria which differ from model to model. (Voyant, 2017) showed that support vector machines (SVM) are a very promising forecasting method and have not been sufficiently investigated by researchers. In addition, the artificial neural network model (ANN) is the most used approach for solar radiation prediction. We have applied the SVM and ANN models to the dataset of Évora city. The obtained outcomes enable us to comprehend better how these ML algorithms perform with the data of this site which leads to enriching the literature.

This article compares SVM and ANN techniques for predicting one hour of global solar radiation using endogenous data from Évora. We have utilized the auto mutual information function to identify delayed values of solar radiation that are the most relevant for prediction. Furthermore, we have performed a comparison study according to three timescales: yearly, seasonally, and daily. These comparisons enable us to comprehend better the performances of the proposed ML models under different meteorological conditions. The final results demonstrate that there isn't just one optimal approach, but the two ML techniques complement each other in such a manner that the SVM approach gives good results on sunny days while the ANN technique performs well on overcast days.

The remainder of this work is structured as follows: Section 2 outlines the suggested technique. Section 3 covers the empirical results, and Section 4 closes the study and offers some future research directions.

2 METHODOLOGY

2.1 Solar Radiation Measurements

In this work, we have used global horizontal solar radiation hourly time series data from 2012 to 2016 to forecast one hour in advance of the solar radiation in Évora (Portugal). These data have been collected from the meteorological station of the Évora city (38°34 N, 07°54 W) using an Eppley pyranometer. In this study, we have used only daytime hours from 6:00 to 20:00. In addition, we have applied the auto mutual information function (AMIF) to identify the delayed values that have a linear and nonlinear relationship with the future values of solar radiation (Benali, 2019; Ali-Ou-Salah, 2021). The results show that eight historical values have a strong correlation with future global solar radiation.

2.2 Support Vector Machines

Support vector machines (SVM) is a supervised learning algorithm used for classification and regression. It was first introduced by Vladimir Vapnik and his co-workers in 1992 (Boser, 1996). SVM has been widely employed by researchers for solar radiation prediction due to its good generalization capabilities and their capacity to lead with nonlinear time series. The nonlinear SVM regression is based on kernel functions that map inputs into high dimensional feature space, in which linear regression is carried out by minimizing the ε-insensitive loss function (Urraca, 2016). Figure 1 shows the nonlinear transformation using a kernel function.

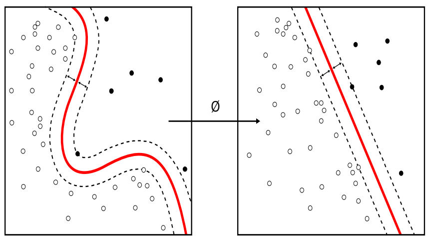


Figure 1: Transformation into high dimensional feature space using the kernel function.

In addition, the SVM also minimizes the model error to increase accuracy. As a result, the SVM minimizes the following function that regroups the ε-insensitive loss function and the model error.

$$min\left(\frac{1}{2}\parallel w\parallel^2+\ C\sum_{i=1}^{n}(\xi_i+\xi_i^*)\right) \tag{1}$$

$$subject\ to\begin{cases} y_i-(\langle w,x_i\rangle+b)\leq\varepsilon+\ \xi_i \\ (\langle w,x_i\rangle+b)-y_i\ \leq\varepsilon+\ \xi_i^* \\ \xi_i,\xi_i^*\ \geq\ 0\ \ clear \end{cases} \tag{2}$$

Where x_i and y_i are respectively the set of inputs and the set of targets. w is the weight vector, and b is the bias. ε is the epsilon margin. ξ_i,ξ_i^* are the slack variables, and C is the cost parameter (Perez, 2010).

The training inputs are mapping into high dimensional feature space using nonlinear mapping function $\varphi(x)$ (Jiménez-Pérez, 2016). In this work, we used the radial basis function (RBF) as a kernel function. The RBF is described as follow:

$$K(x_i,x_j)=\exp(-\parallel x_i-x_j\parallel^2/2\sigma^2) \tag{3}$$

where σ is a free parameter that controls the width of the Gaussian function.

The generalization performance of the SVM model depends on the epsilon margin ε, the cost parameter (C), and the free parameter (σ). We have applied the grid search strategy to determine the best values of ε, C, and σ (Torres-Barrán, 2019).

2.3 Artificial Neural Network

Artificial Neural Network (ANN) is a heuristic model that simulates two human brain functions: learning and generalization. In the first process, the network is trained with examples representing the problem, then the knowledge acquired by the network is tested during the generalization process with unseen examples.

ANN models offer an alternative solution to traditional models that cannot solve complex problems precisely. Their application had been proven effective in various fields such as engineering, telecommunication, economics, medicine, environment, etc. (Safi, 2013). The basic neural network architecture is the feed-forward neural network (FFNN). It comprises three layers: the input layer, one or many hidden layers, and the output layer. Each layer contains many neurons which are interconnected to other layer's neurons by weighted connections (Teo, 2015). Figure 2 shows the single layer FFNN architecture.

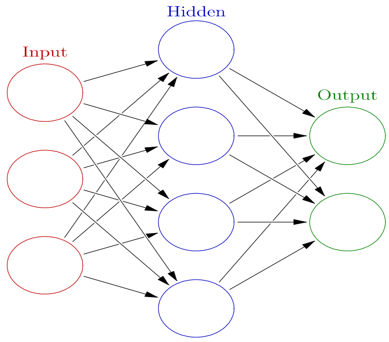


Figure 2: Single layer FFNN architecture.

The process of learning consists of adjusting the connection weights iteratively according to a training algorithm. Among ML algorithms, we find supervised learning techniques that reduce the error between real output and desired output. This operation is repeated until the ANN model reaches an acceptable performance. Subsequently, the generalization process tests the network on new data to evaluate the learning procedure.

The model's accuracy depends on several parameters such as the used dataset, the number of hidden layers, the number of hidden neurons, and the activation functions. Further, the dataset is divided into training, testing and validation sets. The training set is used in the learning process to update network weights and biases, while the validation set is used to stop the training process. The testing set is utilized to test the network performance, which allows comparison between different network architectures. Furthermore, the used training algorithm impacts the learning process significantly; that's why it should be chosen carefully (Teo, 2015). As reported by (Wang, 2011), any nonlinear problem whose samples are not too large can be solved by an ANN network with one hidden layer having a sufficient number of neurons. The number of hidden neurons *(Num_Hidden_neurons)* represents the most critical parameter in network architecture. In addition, the Levenberg Marquardt training algorithm (LM) is used to train the ANN model. This algorithm gives accurate predictions when it is used with hyperbolic tangent sigmoid transfer function in the hidden layer and linear transfer function in the output layer (Yadav, 2014).

2.4 The Architecture of ML Models

The grid search strategy was applied to determine the best architectures of the SVR and ANN models. Several combinations of user-defined hyperparameters were investigated to identify the best model with the lowest 5-fold cross-validation error (Ali-Ou-Salah, 2021). In reality, the 5-fold cross-validation approach splits the dataset randomly into five folds (Mellit, 2010; Hassan, 2017). Each fold is used as a testing set, and the rest folds are used as a training set. Each fold serves as a testing set, while the remaining folds serve as a training set. The average of the errors of all testing sets is the 5-folds cross-validation error. Figure 3 depicts the grid search technique's steps.

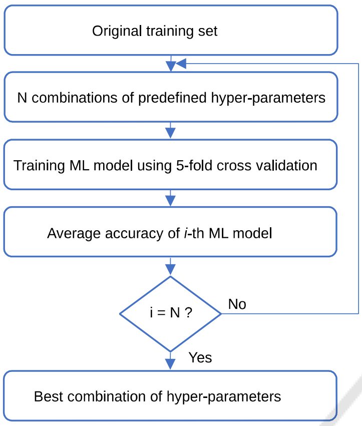


Figure 3: The grid search technique.

The 'fitnet' function was used for the ANN method, whereas the 'fitrsvm' function was utilized to design the SVR approach. These functions are available in the Statistics and Machine learning Toolbox of Matlab software. The ranges of hyperparameters for the SVR and ANN model are as follow:

For the ANN model:

- *Hidden_neurons* = [10, 20, 30, 40, 45, 50, 55, 60, 65, 70, 75, 80, 90, 100]

For the SVR model:

- C = [100, 200, 300, 400, 500, 600, 700].
- ε = [10, 20, 30, 40, 50, 60, 70].
- σ = [0.5, 1.23, 1.5, 2, 3].

2.5 Statistical Indicators

The proposed models have been evaluated using the root mean square error (RMSE), the normalized root mean square error (nRMSE), the mean absolute error (MAE) and the normalized mean absolute error (nMAE) (Benali, 2019; Voyant, 2017). The lower their values, the more the forecasts are accurate.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{4}$$

$$nRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}}{\frac{1}{n}\sum_{i=1}^{n} y_i} \times 100 \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{6}$$

$$nMAE = \frac{\frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|}{\frac{1}{n}\sum_{i=1}^{n} y_i} \times 100 \tag{7}$$

3 RESULTS AND DISCUSSION

In this study, the auto mutual information function was utilized to identify the most relevant historical values for predicting one hour in advance of solar radiation. Indeed, the obtained findings demonstrate that eight delayed variables may predict future solar radiation reliably. Moreover, the optimal architecture of the SVM and ANN models was determined using the 5-fold cross-validation approach. For the SVM model, different combinations of C, ε, and γ have been tested to find the optimal combination that gives the best 5-fold cross-validation error. Similarly, different values of neurons have been utilized to find the best number of neurons of the ANN model. Table 1 summarizes the obtained architectures of the SVM and ANN models.

Table 1: Architectures of the SVM and ANN models.

Mdl	Configuration	RMSE (W/m^2)
SVM	$C = 600;\ \varepsilon = 10;\ \sigma = 2$	62.35
ANN	*Num_Hidden_Layers* = 1; *Num_Hidden_neurons* = 60	63.82

3.1 Annual Analysis

Using one year of the testing set, a comparison of the SVM and ANN techniques was carried out. The results of the yearly comparison between the SVM and ANN approaches are presented in Table 2.

Table 2: The outcomes of the yearly comparison of the SVM and ANN techniques.

Error metrics	SVM	ANN
RMSE (W/m^2)	62.80	**62.73**
nRMSE (%)	18.73	**18.70**
MAE (W/m^2)	**32.52**	33.94
nMAE (%)	**9.69**	10.12

As shown in Table 2, According to nRMSE, the ANN method outperforms the SVM approach. However, in terms of nMAE, the SVM technique outperforms the ANN method. In reality, comparing these two ML techniques appears to be challenging because the ANN method performs well according to nRMSE while the SVM approach performs well according to nMAE.

As a result, an in-depth comparative analysis of the SVM and ANN techniques was conducted utilizing seasonal testing sets to evaluate the prediction performance of each ML approach according to seasons.

3.2 Seasonal Analysis

The testing set is divided into four testing subsets, each representing a different season of the year. For each season, Table 3 summarizes the findings of the comparison between the SVM and ANN techniques.

Table 3: A comparative study between the SVM and ANN techniques utilizing testing subsets based on seasons.

Error metrics	Winter		Spring		Summer		Autumn	
	SVM	ANN	SVM	ANN	SVM	ANN	SVM	ANN
RMSE (W/m^2)	**48.76**	50.06	94.43	**93.89**	42.01	41.97	51.97	**51.42**
nRMSE (%)	**24.31**	24.96	22.84	**22.71**	8.41	8.40	23.76	**23.51**
MAE (W/m^2)	**27.84**	29.12	**57.09**	59.04	**17.88**	20.24	**27.36**	27.42
nMAE (%)	**13.88**	14.52	**13.81**	14.28	**3.58**	4.05	**12.51**	12.54

As shown in Table 3, it is found that the SVM model gives better results than the ANN model in the winter in terms of nRMSE and nMAE. Moreover, the SVM approach outperforms the ANN in terms of nMAE, and they have slightly the same nRMSE in summer. Finally, in spring and autumn, the ANN is slightly better than the SVM according to nRMSE, but the SVM approach outperforms the ANN according to nMAE. This finding does not allow us to conclude the most efficient ML technique for the spring and autumn seasons. As a result, a more comparative study based on daily testing sets is necessary, to investigate more deeply the performance of each ML technique.

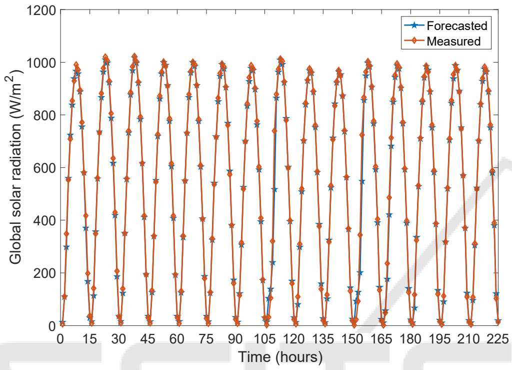
3.3 Daily Analysis

Daily testing sets generated from the daily categorization of global solar radiation were used to compare the SVM and ANN techniques. This classification was performed using the daily clearness index (kt), which is given as the daily quotient between global solar radiation and extraterrestrial radiation. (Yousif, 2013). Several kt intervals have been employed to classify the daily sky conditions into two types: sunny or very sunny sky conditions ($kt > 0.6$) and overcast or partly cloudy sky conditions ($kt \leq 0.6$) (Yousif, 2013). Then, using the daily clearness index of Évora city provided by power project data sets supported by NASA (The POWER Project, 2021), one year of testing data was split into two daily testing subassemblies. The findings of the comparison between the SVM and ANN models utilizing 147 overcast days and 219 sunny days are shown in Table 4.

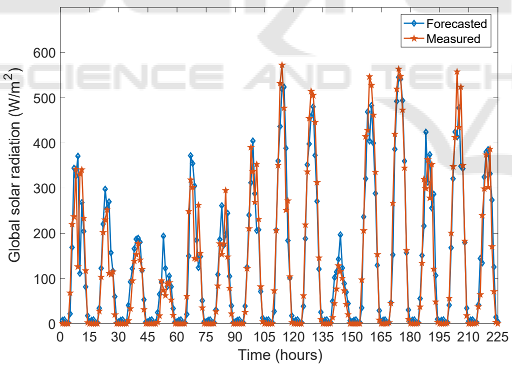
Table 4: Comparison between the SVM and ANN models using daily testing sets.

Statistical indicators	Sunny days ($kt > 0.6$)		Cloudy days ($kt \leq 0.6$)	
	SVM	ANN	SVM	ANN
RMSE (W/m^2)	**38.80**	40.77	87.05	**85.56**
nRMSE (%)	**9.15**	9.61	42.82	**42.09**
MAE (W/m^2)	**19.72**	22.47	51.58	**51.02**
nMAE (%)	**4.65**	5.30	25.37	**25.1**

Table 4 compares the SVM and ANN models using sunny and cloudy testing sets. For sunny days, the SVM outperforms the ANN model according to nRMSE and nMAE. In contrast, for cloudy days, the ANN yields better results than the SVM in terms of nRMSE and nMAE. Unlike the annual and seasonal comparisons, the daily comparison better shows the forecasting accuracy of each model, allowing us to draw firm conclusions about the ANN and SVM models. Consequently, a novel hybrid model is created by combining the SVM model for sunny days and the ANN model for cloudy days. Figure 4 shows the forecasted values versus the measured values using the ANN and SVR techniques for predicting one hour in advance of global solar radiation.



(a)



(b)

Figure 4: Forecasted values versus measured values using the ANN model with cloudy days (a) and the SVR model with sunny days (b).

Performance comparison with the existing approaches in recent literature has been performed. Table 5 shows the annual comparison of one hour in advance of global solar radiation prediction between the developed hybrid method and the other approaches available in the recent literature (Benali, 2019; Benmouiza, 2019; Ibrahim, 2017). The proposed hybrid model outperforms the models of other studies according to the nRMSE and RMSE. The suggested hybrid model takes advantage of both SVR and ANN models and uses them to forecast daily data in which they perform well. The limitations of this work are the lack of some important meteorological variables such as the clearness index and the low computing capacity that allow us to find more optimal ML architectures.

4 CONCLUSIONS

This study offers a novel hybrid method for predicting one hour in advance of global horizontal solar radiation in the region of Évora based on the SVR and ANN techniques. In fact, the auto mutual information function was utilized to identify the most relevant delayed values of solar radiation, allowing for reliable prediction of future values. In addition, different comparisons have been carried out to highlight the performances of each model. Firstly, an annual comparison study between the SVM and ANN models has been conducted using one year of the testing set. The results show that the ANN approach is superior to the SVM technique in terms of nRMSE, while the SVM technique is superior in terms of nMAE.

Subsequently, a seasonal comparison study has been undertaken using four seasonal testing subsets. It has been found that the SVM gives better results than the ANN for the winter and summer seasons. Further, in spring and autumn, it has been demonstrated that comparing ML techniques is challenging because there is a discrepancy between the nRMSE and the nMAE. For this reason, a daily comparison study has been performed using daily testing subsets. Using the daily clearness index, one year of testing data was split into two daily testing subgroups. The results indicate that, for sunny days, the SVM model performs better than the ANN model. In contrast, for cloudy days, the ANN model outperforms the SVM method. Based on these results, it can be concluded that the daily assessment of ML techniques is the most effective method to evaluate the forecasting accuracy of the suggested ML models.

Further work will focus on comparing the suggested hybrid methods with deep learning and recurrent neural network techniques, which are very promising ML approaches.

Table 5: Annual comparison of the proposed models with the approaches in the recent literature.

Study	Models	Locations	nRMSE (%)	RMSE (W/m^2)
(Benali, 2019)	RF	France	19.65	88.62
(Benmouiza, 2019)	FCM-ANFIS	Algeria	NA	112
(Ibrahim, 2017)	RF-FA	Malaysia	18.97	68.84
This paper	Hybrid model	Portugal	**18.70**	**62.73**

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