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# Solar Intensity Forecasting using Artificial Neural Networks and Support Vector Machines

L. Marques[a], T. Pinto[a], T. M. Sousa[a], I. Praça[a], Z. Vale[a,]*, S. L. Abreu[b]

[a] *GECAD – Knowledge Engineering and Decision Support Research Center, Institute of Engineering – Polytechnic of Porto (ISEP/IPP), Rua Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal*

[b]*General – Alternative Energies Grooup - IFSC – Instituto Federal de Santa Catarina - Campus São José, Rua José Lino Kretzer, 608 - Praia Comprida - CEP 88103-310 - São José, Brazil*

**Abstract**

This paper presents several forecasting methodologies based on the application of Artificial Neural Networks (ANN) and Support Vector Machines (SVM), directed to the prediction of the solar radiance intensity. The methodologies differ from each other by using different information in the training of the methods, i.e, different environmental complementary fields such as the wind speed, temperature, and humidity. Additionally, different ways of considering the data series information have been considered. Sensitivity testing has been performed on all methodologies in order to achieve the best parameterizations for the proposed approaches. Results show that the SVM approach using the exponential Radial Basis Function (eRBF) is capable of achieving the best forecasting results, and in half execution time of the ANN based approaches.

Keywords: Artificial Neural Networks, Data Mining, Machine Learning, Solar forecasting, Support Vector Machines

## 1. Introduction

The use of renewable energy sources is having a significant increase in the last decades, encouraged by governmental policies and incentive programs whose concern is to avoid the exploitation of finite fossil fuel reserves and at the same time avoid environmental damages.

In Europe a set of legislation was defined having the known “20-20-20” as targets. The national targets will enable the EU as a whole to reach its 20% renewable energy target for 2020 - more than double the 2010 level of 9.8%. These targets, which reflect Member States' different starting points and potential for increasing renewables production, range from 10% in Malta to 49% in Sweden [1].

In this context alternative sources of renewable and clean energy, such as tidal, wind and solar have become of great importance. However the variable and intermittent nature of these resources poses a lot of challenges to several entities such as utility companies, power systems operators and market operators, especially when considering a significant market penetration rate as it expected and encouraged to

* Corresponding author
*E-mail address:* zav@isep.ipp.pt

achieve.

Solar energy is clearly the most abundant resource available to modern societies. Usually summer months, such as July and August in the northern hemisphere, have smaller variability. However, even during some sunshine months sudden changes might occur. The variability of the solar resource is mostly due to cloud cover variability and atmosphere conditions.

The contribution of this paper is the understanding and improvement of the solar irradiance forecasting, given its particular variability. For this, several forecasting methods, based on Artificial Neural Networks (ANN) and Support Vector Machines (SVM), are proposed and conclusions about the solar irradiance components and algorithms' parameters are taken. An hybrid approach, that combines ANN and SVM with a clustering algorithm that is used to filter the data that is most appropriate to be used in the training process of the forecasting methodologies is proposed and proved to be an interesting area of research, capable of improving ANN or SVM results. The usage of the specific historical data that most potentiates the optimization of the forecasting methods proves to have an equal or even higher importance than the optimization of the methodologies' parameters themselves.

Section 2 presents an overview of solar forecasting importance with particular emphasis to the smart grids and microgrids concepts. Section III highlights solar irradiance components and presents ANN and SVM techniques. In section IV experimental findings about the proposed methods and the obtained conclusions are presented and discussed. Real data from solar irradiance values of Florianópolis, in Santa Catarina, Brazil have been used in the experiences. Finally, section 5 presents the most relevant conclusions and contributions of this work.

## 2. Solar Forecasting

Despite its importance for the existence of life on earth, and human beings health, the sun is nowadays a source of clean energy and can contribute to reduce the difficulty in fulfilling the energy demand. Photovoltaic (PV) and solar thermal are the main sources of electricity generation from solar energy. In the case of solar thermal energy plants with storage energy system, its management and operation need reliable predictions of solar irradiance with the same temporal resolution as the temporal capacity of the back-up system [2]. The development in the power semiconductor technology has allowed higher efficiencies in the conversion of solar energy into electrical energy through photovoltaic cells [3] and PV systems have reached the end-user. The spread of PV technology took place initially in rural areas, but has nowadays been used to be integrated into roofs and facades of buildings to generate electricity.

The increase on the use of renewable energy sources (RES) affects the behavior of a considerable number of entities from the electricity sector and imposes economical and technical challenges. Forecasting renewable resources is important from the producers, retailers, aggregators, system operators and market operators point of view.

From the utility point of view, application of renewable sources can potentially reduce the demand for distribution and transmission facilities. Clearly, distributed generation located close to loads can reduce power flows in transmission and distribution circuits with two important effects: loss-reduction and the ability to potentially substitute for network assets. Furthermore, the presence of generation close to demand could increase service quality seen by end customers [4].

From the power system operators point of view, short-term forecasting is relevant for dispatching and regulatory purposes, to optimize the decision making by allowing corrections to unit commitment.

Concerning market operators, the prevision of the production is important for planning transactions in the electricity market in order to assure the balancing between supply and demand. From the economical point of view it is also important for electricity players to use this knowledge as competitive advantage in day-ahead electricity trading.

The balancing market is a complementary market to the day-ahead market, which allows agents to adjust their needs and renegotiate previously agreed energy by adjusting the quantities traded in the daily market. This enables players to overcome fluctuations of the production forecasts, which is particularly important for producers based on RES, such as wind and solar power, due to their variable and intermittent nature.

Solar, wind and load forecasting have become integral parts of the smart grid and microgrid concepts.

### *2.1. Smart grids and microgrids*

According to the European Technology Platform of Smart Grids [5], a smart grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that assume both roles – in order to efficiently deliver sustainable, economic and secure electricity supplies. A key goal of smart grids efforts is to substantially increase the penetration of environmental friendly energy sources, such as solar.

Microgrids, also characterized as the "building blocks of smart grids", comprise low voltage distribution systems with distributed energy resources (DER) (microturbines, fuel cells, PV, etc.) together with storage devices (flywheels, energy capacitors and batteries) and flexible loads [4]. Microgrids can be operated in a non-autonomous way, if interconnected to the grid, or in an autonomous way, if disconnected from the main grid.

The production sources within a microgrid can be dispatchable or intermittent for certain RES technologies, such as PVs and small wind turbines. Controllability of these intermittent units is limited by the physical nature of the primary energy source. Moreover, limiting RES production is clearly undesirable due to the high investment and low operating costs of these units and their environmental benefits over carbon emission. Consequently, it is generally not advisable to curtail intermittent RES units, unless they cause line overloads or overvoltage problems.

Solar irradiance forecasting is important for the integration of this source of renewable energy into these new concepts of electrical grid, to help grid operators to optimize RES production usage and/or reduce additional costs by preparing an appropriate strategy [6, 7].

## 3. Data and Methods

Here we review some fundamental concepts about solar irradiance components, related work on solar forecasting and the artificial intelligence techniques that we have used in this study and documented experiences.

### *3.1. Solar Irradiance Components*

The solar irradiance fluctuates around an average value of approximately 1360Wm-2 [8]. The incident extraterrestrial beam radiation is divided in two distinct components: the Direct Normal Irradiance (DNI) and the Diffuse Horizontal Irradiance (DHI). The geometric sum of both results is the Global Horizontal Irradiance (GHI) that can be written as:

$$GHI = DHI + DNI*\cos\theta \tag{1}$$

where $\theta$ is the solar zenith angle. The extraterrestrial irradiation is measured above the Earth's atmosphere, so it is not influenced by clouds in the atmosphere and can easily be previewed throughout the year [9].

### *3.2. Solar Forecast*

Usually, to predict renewable sources of energy two approaches may be used: an approach based on physical models [10], using mathematical equations to describe physics and dynamics of the atmosphere that influences solar radiation, and an approach based on time series analysis by means of statistical models [11]. Physical models work well for medium- and long-term solar forecasting, while statistical models have lower complexity and can perform well for short-term solar intensity forecasting.

In this work we focus on the second approach, thus on the analysis of an historical database by means of statistical analysis and learning methods, for short-term solar forecasting.

Several techniques have been applied to solar irradiation or solar power forecast such as regression techniques, Auto Regressive Moving Averages (ARMA), Auto Regressive Integrated Moving Averages (ARIMA), Artificial Neural Netwroks (ANN), Genetic Algorithms (GA) and Support Vector Machines (SVM).

References [9], [12] and [13] provide good overviews on the current state of the art in solar irradiance forecasting. In [14] a comparison on several forecasting techniques to predict solar power at a photovoltaic power plant in California is presented. In this work, ANN has proved to be a promising technique on this field, showing improved results while combined with GAs. The same conclusions about the use of ANNs were achieved by [15] and [16]. ANNs have also been successfully applied to the forecasting of other renewable sources based production types, such as the wind power, in [17]. The good results achieved by ANNs in the most varied fields [18, 19, 20, 21], provide an encouraging indication of ANNs' capability of coping with the problem approached in this work.

In [22], [23] and [24] the use of SVM proved to be a promising technique to solar forecasting research.

Based on these previous studies ANN and SVM are used as the basis for the present work on investigating the most relevant components of solar irradiance and other meteorological variables.

The accuracy of the forecast may be evaluated by several error indices, such as the mean absolute error (MAE), the mean absolute percentage error (MAPE), the symmetric mean absolute percentage error (SMAPE) and the standard deviation (SD) [25].

### *3.3. Artificial Neural Networks*

Artificial Neural Networks (ANN) are inspired on the human brain and on how their neurons process information with high interconnectivity. ANNs are constituted by several nodes, or neurons, organized in different levels, and interconnected by numeric weights. They resemble to the human brain in two fundamental points: the knowledge being acquired from the surrounding environment, through a learning process; and the network's nodes being interconnected by weights (synaptic weights), used to store the knowledge. Each neuron executes a simple operation, the weighted sum of its input connections, which originates the exit signal that is sent to the other neurons. The network learns by adjusting the connection weights, in order to produce the desired output - the output layer values [26].

Based on a large number of correct examples ANN are able to change their connection weights until they generate outputs that are coincident with the correct values. By this way, ANN are able to extract basic rules from data [27].

### *3.4. Support Vector Machines*

In 1936, R. A. Fisher [28] created the first algorithm for pattern recognition. The SVM algorithm is implemented by a generalization of the nonlinear algorithm Generalized Portrait that has been created by Vapnik and Lerner in the sequence of [29]. This was the first running kernel of SVM, only for classification and linear problems.

The SVM concept can be tracked to when statistical learning theory was developed further with Vapnik, in 1979. However, the SVM approach in the current form was first introduced with a paper at the COLT conference, in 1992 [30].

Some essential aspects to take into account when implementing a SVM based methodology are the feature space, the loss functions [31], and the kernel functions. The most applicable kernels for time series forecasting, as is the problem approached in this paper, of solar forecasting, are the Radial Basis Function (RBF) and the exponential Radial Basis Function (eRBF). These two kernels are specifically directed to regression in time series data.

## 4. Experimental Findings

This section shows the results of the tests that have been performed to assess the functioning of the methodologies and their parameters' tuning for better results achieving. All tests were performed for the same day and period, in order to conclude which is the most appropriate methodology for the day and period under analysis.

This section is divided into three parts, namely: (i) results of the ANN based methodologies; (ii) results of the SVM based methodologies; (iii) execution times comparison. This comparison allows reaching relevant conclusions about the best methodology to forecast solar intensity.

The used data are referent to Florianópolis, state of Santa Catarina, Brazil. These data correspond to the period from 1990 to 1999, including the values of Global, Direct, Diffuse and Extraterrestrial Irradiance, in W/m2; temperature in ºC; humidity in %; and wind speed in m/s. more details in the used data can be found in [32].

### *4.1. ANN Methodologies*

Equally important to an adequate parameterization of the used forecasting methodology is the suitable interpretation of the used data. Time series data can be interpreted in many different ways, and data sequences can be looked at from different perspectives. For this reason various forecasting methodologies based on ANN have been developed. After exhaustive preliminary tests to choose the most suitable forecast input data, three promising solutions have been found. The authors have decided to implement these three solutions with the goal of studying and concluding which would achieve the best performance.

These three solutions, or topologies, use as input data:

- M1 - last 4 periods, i.e. use the 4 hours before the time that is intended to forecast;
- M2 - last 24 periods, i.e. use the 24 hours preceding the time of day that is intended to forecast;
- M3 - last 7 days, i.e., using data exclusively from the same hour that is intended to forecast, but corresponding the 7 previous days to the day intended to forecast.

Moreover, another issue concerning data types (fields) that influence the solar intensity has emerged. As already mentioned, the fields that are part of the historical records of solar data are: I_Glob_H (Global Horizontal Irradiance), I_Beam_N (Direct Normal Irradiance), I_Diff_H (Diffuse Horizontal Irradiance), I_Extr_H (Extraterrestrial Horizontal Irradiance), Temp (Temperature), Rel_Humidity (Humidity), Wind_Speed (Wind speed).

In order to implement, test and take conclusions, four different sets of fields have been used in the forecasting process. This way it is possible to realize which fields provide added value for the forecasting process. The four sets are:

- SM1 – only each of the four solar intensity fields independently (I_Global_H, I_Beam_N, I_Diff_H or I_Extr_H) ;
- SM2 – the four principal fields simultaneously (I_Global_H, I_Beam_N, I_Diff_H and I_Extr_H) ;
- SM3 – all fields (I_Global_H, I_Beam_N, I_Diff_H, I_Extr_H, Temp, Rel_Humidity and Wind_Speed);
- SM4 – The main field (I_Global_H) used with the three complementary fields (Temp, Rel_Humidity and Wind_Speed).

Thus, each of the three methodologies (last 4 periods, last 24 periods, and last 7 days), is subjected to four sub-methodologies (SM) based on the 4 datasets that were described before.

The sensitivity analysis consisted in a huge amount of tests, with the purpose of reaching the most advantageous combination of parameters. The parameters that have presented the higher influence on the results are: the number of nodes in the ANN’s hidden layer, and the training limit, i.e. the amount of training data. Figure 1 presents the results of the variation of the number of intermediate layer nodes, when using each of the four fields of solar irradiance independently for the forecast, namely: I_Global_H, I_Beam_N, I_Diff_H and I_Extr_H. Figure 2 presents the SMAPE (%) error variation for different amounts of training data.

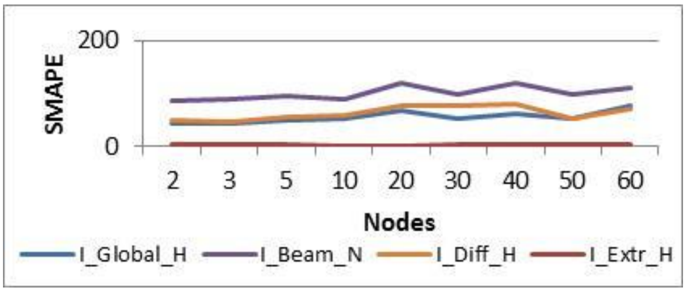


Figure 1 – Forecasting error for different numbers of intermediate nodes, for each solar field

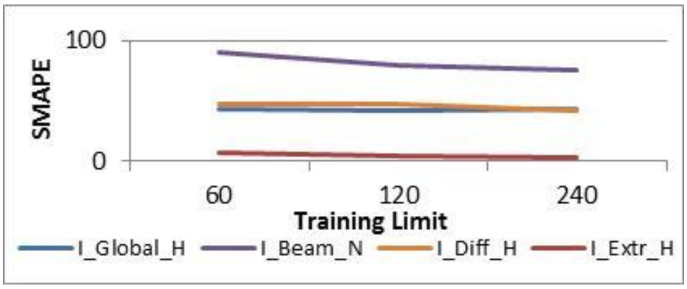


Figure 2 – Forecasting error for different amounts of training data, for each solar field

From Figure 1 and Figure 2 it is visible that the best combination would be to use 3 intermediate nodes with a training limit of 120. Figure 1 shows that the increase of the hidden layer nodes instigates an increase of the forecasting error values in three from the four solar intensity data types. Three nodes is the number that presents the best overall results for the four fields. Regarding the training limit, one can see from Figure 2 that the SMAPE values stabilize after the value of 120. This means that it is irrelevant to include a larger amount of training data, as the increase in training execution time does not bring any added value for the quality of the forecasts.

Thus 3 intermediate layer nodes and a training limit of 120 are the values that are used for all ANN based methodologies. Table 1 shows the SMAPE (%) error values of the first topology (M1).

Table 1 – SMAPE error values obtained in the forecasts using M1 (with the last 4 periods), in %

| | *I_Glob_H* | *I_Beam_N* | *I_Diff_H* | *I_Extr_H* |
|---|---|---|---|---|
| *M1 - SM1* | *39,81* | *81,49* | *38,24* | *1,16* |
| *M1 - SM2* | *37,22* | *76,19* | *47,68* | *7,00* |
| *M1 - SM3* | *43,67* | *81,82* | *34,6* | *8,16* |
| *M1 - SM4* | *40,14* | - | - | - |

In SM4 only the I_Glob_H field is forecasted, therefore, Table 1 does not show the error value concerning the other solar intensity fields. For M1, one can see that the best results in forecasting the I_Glob_H field are achieved when using the four solar intensity fields at the same time, for the forecasting process (SM2). Table 2 shows the SMAPE (%) forecasting results, referring to the second topology (M2).

Table 2 – SMAPE error values of the M2 topology, in %

| | *I_Glob_H* | *I_Beam_N* | *I_Diff_H* | *I_Extr_H* |
|---|---|---|---|---|
| *M2 - SM1* | *34,02* | *74,81* | *46,14* | *2,69* |
| *M2 – SM2* | *54,57* | *100,6* | *47,43* | *7,86* |
| *M2 – SM3* | *47,43* | *92,87* | *92,81* | *9,92* |
| *M2 – SM4* | *46,27* | - | - | - |

From Table 2 it is visible that, concerning the forecast errors' analysis using the last 24 periods, using only one solar field (SM1) leads to obtaining better predictions. Table 3 presents the results of M3.

Table 3 – SMAPE error of the forecasts using the last 7 days – M3, in %

| | *I_Glob_H* | *I_Beam_N* | *I_Diff_H* | *I_Extr_H* |
|---|---|---|---|---|
| *M3 - SM1* | *44,4* | *83,08* | *61,4* | *0,52* |
| *M3 – SM2* | *48,96* | *74,28* | *49,72* | *8,67* |
| *M3 – SM3* | *53,19* | *109,87* | *49,03* | *9,91* |
| *M3 – SM4* | *39,86* | - | - | - |

From table 3, concerning the forecast error analysis with the last 7 days, we concluded that using one solar field (SM1) leads to obtaining better forecasts, precisely because it gets the best global solar intensity forecast.

Finally, to conclude the ANN tests analysis, in the first methodology, using the last 4 periods it was concluded that using the 4 solar fields obtain better forecasts, with and error of 37,22% for I_Glob_H parameter. In the second methodology, using the last 24 periods best forecasts are obtained using one solar field, with an error of 34,02% for the parameter I_Glob_H. Finally, the third methodology using the same period of last week, obtains better predictions using one solar field, with an error of 44,4% for the parameter I_Glob_H. The methodology which achieved better forecast, as can be seen by calculating the error, was the second, using the last 24 periods, and the first sub-methodology, using only the I_Glob_H field as training data, while ignoring the other (M2 – SM1), with a SMAPE value of 34,02.

*4.2. SVM Methodologies*

Similarly to the ANN based methodologies, more than one approach has been considered, regarding the input data to train the SVM. Two solutions have been implemented, which use as input:

- SVM_M1 - the same period in the last days, i.e., using data from the same hour that is forecasted, but in the last days preceding the day to forecast;
- SVM_M2 - last hours, i.e. use the latest hours before the hour of the day that is being forecasted.

Considering the conclusion taken from the performance of the ANN based approach that the use of the I_Glob_H field by itself leads to better forecasting results, and given the intrinsic nature of SVM, which assumes a single data series prediction; only the historical data of the I_Glob_H field is used by the SVM based approaches.

Sensitivity tests have been performed in order to determine the best parameterizations for the SVM approach. The most influential parameters on the results are: the kernel function, the angle of the kernel function – σ, and the amount of training data – training limit. Regarding the kernel functions, as mentioned before, the most suitable kernel functions for time series prediction are the RBF and eRBF kernels; therefore, these two kernels have been used.

Figure 3 and Figure 4 present the evolution of the MAE and SMAPE error values for different training limits and σ respectively, when using the SVM approach with the RBF kernel.

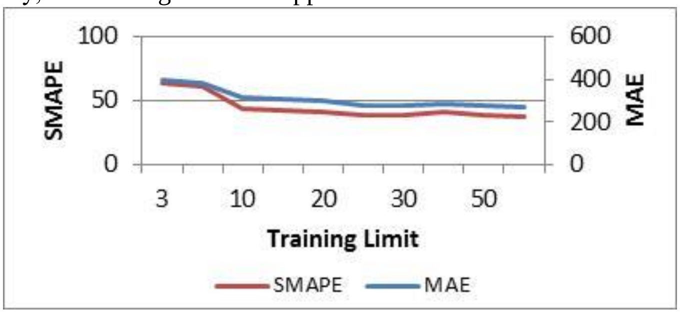


Figure 3 – Forecasting error for different training limits, when using the SVM approach with the RBF kernel

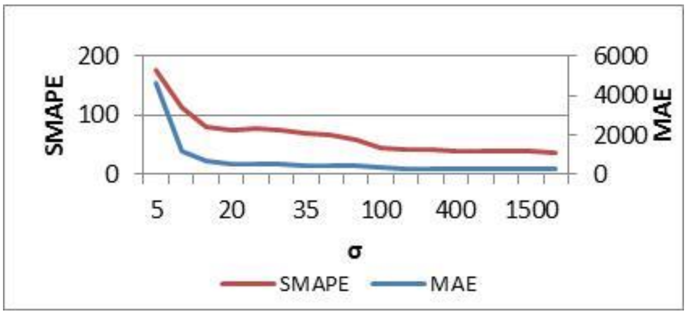


Figure 4 – Forecasting error for different kernel function angles, when using the SVM approach with the RBF kernel

From Figure 3 and Figure 4 it can be concluded that the use of the SVM methodology with the RBF kernel achieves the best results with a training limit of 25 and σ equal to 1000.

Figure 5 and Figure 6 present similar sensitivity analysis results for the SVM approach using the eRBF kernel.

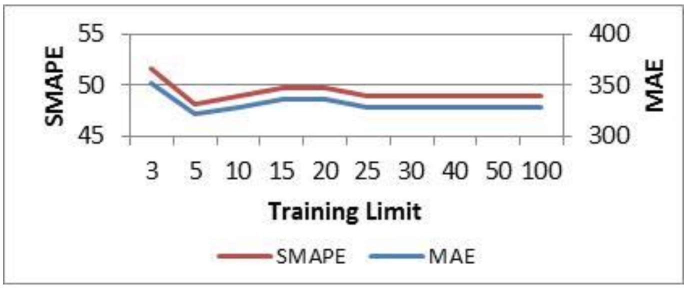


Figure 5 – Forecasting error for different training limits, when using the SVM approach with the eRBF kernel

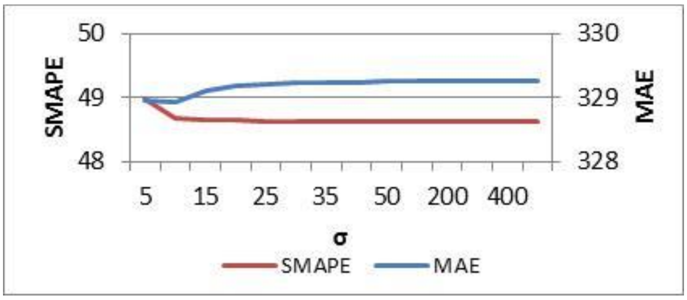


Figure 6 – Forecasting error for different kernel function angles, when using the SVM approach with the eRBF kernel

From Figure 5 and Figure 6 it can be concluded that the use of the SVM methodology using the eRBF kernel reaches its optimal performance with the training limit value of 25 and σ of 10.

Table 4 presents the Standard Deviation (SD), MAE and SMAPE (%) error values of the SVM methodology for the I_GLOB_H solar irradiance field.

Table 4 – SMAPE error of the forecasts using the last 7 days – M3

| *Methodology* | *Kernel* | *SD* | *MAE* | *SMAPE* |
|---|---|---|---|---|
| *SVM_M1* | *RBF* | *229,5* | *270,77* | *38,37* |
| | *eRBF* | *301,56* | *328,97* | *48,99* |
| *SVM_M2* | *RBF* | *317,12* | *179,7* | *23,36* |
| | *eRBF* | *287,4* | *151,62* | *21,48* |

From Table 4 it is visible that the second methodology (SVM_M2) achieves better forecasting results than SVM_M1, for both kernel functions. Additionally, despite the use of the RBF kernel being able to provide better results with the SVM_M1 methodology, the eRBF kernel was able to achieve better results with the SVM_M2 methodology, and also the global best ones of the SVM based methodologies. Therefore the conclusion is that using SVM_M2 with the eRBF kernel is the solution capable of reaching the best solar irradiance forecasts.

Finally, comparing the SVM approach with the ANN methodologies (which best result has been achieved by the M2 – SM1 methodology, with a SMAPE value of 34,02%), one can conclude that the SVM_M2 methodology with the eRBF kernel is the best overall approach, with a SMAPE of 21,48%.

### *4.3. Execution Times*

The computational effort has been measured for both ANN and SVM methodologies. The parameter that, obviously, presents the higher influence over the execution time of both approaches is the training limit.

All tests have been executed on a machine with the following characteristics: Intel® Xenon® CPU X5450 3,00Ghz (2 processors), 4,00GB of RAM memory and a 32bits operating system.

Figure 7 presents the evolution of the average execution time after 1000 runs for the ANN M2-SM1 methodology.

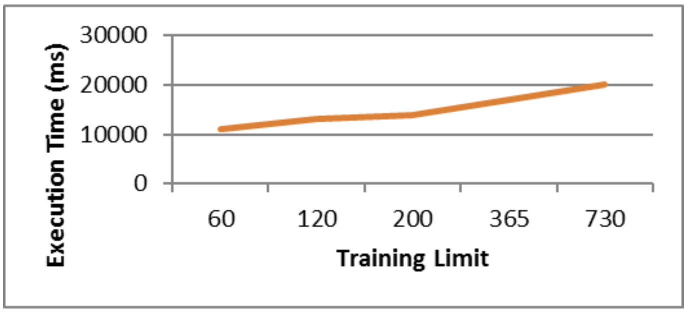


Figure 7 - Average execution time of the ANN M2-SM1 methodology

From Figure 7 is it visible that the execution time increases with the increase of the training limit. As presented in section 4.1, the ANN M2-SM1 methodology has been executed with a training limit of 120, which means an execution time of approximately 13500ms. The use of a higher training limit can produce a computational cost of 20000ms, while using a very low training limit takes nearly 10000ms to execute.

Figure 8 presents the average execution time after 1000 runs, for the SVM based methodologies.

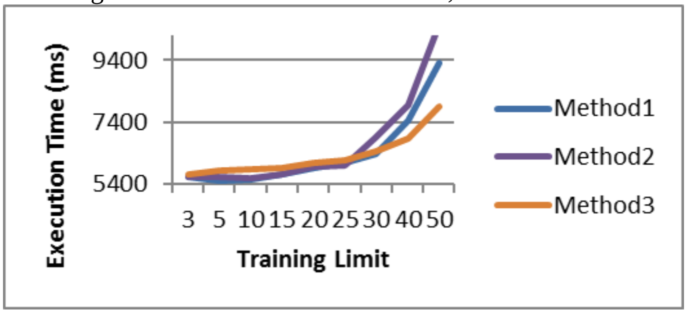


Figure 8 - Average execution time for methodologies based on SVM (Metodology1 that uses the same period of the last days, Metodology2 that uses the latest hours of day and Metodology3 where Clustering is applied), depending on the Training Limit

From Figure 8 it is visible that the SVM based approaches using the training limit of 25 (the optimal value for both kernels as presented in section 4.2) require nearly 6000ms to run. This value is less than half of the time of the ANN based approaches. Even with a very high training limit, the execution time of the SVM approaches is always lower than the faster ANN approaches.

## 5. Conclusions

This paper presented several forecasting methodologies based on the application of ANN and SVM, directed to the prediction of the solar radiance intensity. The methodologies differ from each other by using different information in the training of the methods, i.e, different environmental complementary fields such as the wind speed, temperature, and humidity. Additionally, different ways of considering the data series information has been considered. Sensitivity testing has been performed on all methodologies in order to achieve the best parameterizations for the proposed approaches.

From all the presented tests one can conclude that, for the approached problem of solar intensity forecasting, the use of additional data fields other than the I_Glob_H historic values, brings no added value to the forecasting process. In fact, the forecasting error increases when using additional information.

The ANN based methodology that achieved the best results uses the last 24 periods, and the first sub-methodology, using only the I_Glob_H field as training data, while ignoring the other (M2 – SM1), with a SMAPE value of 34,02%.

Regarding the SVM based methodologies, the eRBF kernel has shown to be the most suitable for this case. While the second methodology, using only the last hours before the hour of the day that is being forecasted, achieved the best results, with a SMAPE of 21,48%. SVM approaches achieved better forecast results than the ANN.

Regarding the execution time of the considered approaches, the SVM based methodologies present an execution time of about half the value of the ANNs.

As future work, the use of other forecasting methodologies, such as fuzzy inference systems can be mentioned. Additionally, the refinement of the ANN and SVM methodologies may lead to an improvement of the results.

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