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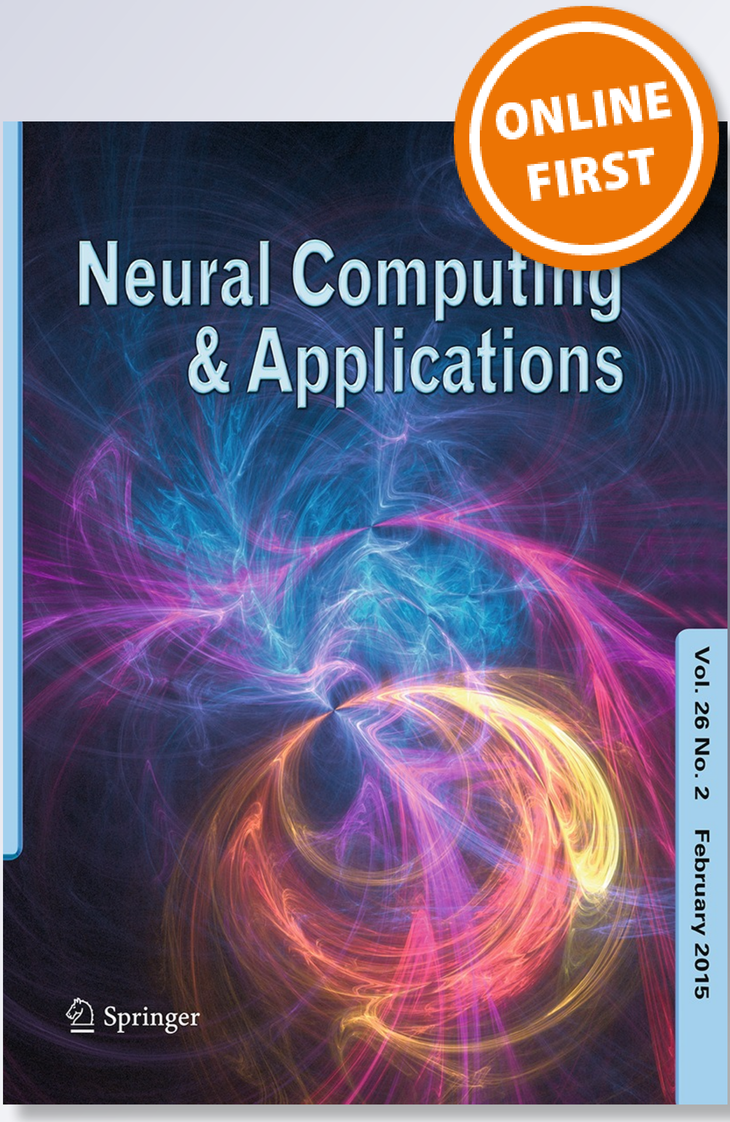

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ORIGINAL ARTICLE

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Abstract Forecasting models for photovoltaic energy production are important tools for managing energy flows. The aim of this study was to accurately predict the energy production of a PV plant in Italy, using a methodology based on support vector machines. The model uses historical data of solar irradiance, environmental temperature and past energy production to predict the PV energy production for the next day with an interval of 15 min. The technique used is based on ν-SVR, a support vector regression model where you can choose the number of support vectors. The forecasts of energy production obtained with the proposed methodology are very accurate, with the R^2 coefficient exceeding 90 %. The quality of the predicted values strongly depends on the goodness of the weather forecast, and the R^2 value decreases if the predictions of irradiance and temperature are not very accurate.

Keywords Forecasting model · Support vector machines · PV energy production

1 Introduction

During the last years, researches on sustainable energy consider the growing use of renewable sources as a strategic option. Therefore, an increasing attention has been devoted to the energy production from renewable sources, because they represent a valid alternative to the traditional fossil fuel resources, whose future availability is uncertain and whose cost is constantly increasing. One of the main renewable energy sources available in nature is the sun, usable for the direct production of electricity through photovoltaic (PV) systems. Besides being an inexhaustible resource in nature, PV solar energy is an example of clean and directly available energy that can be simply obtained by exploiting the radiation from the sun to the Earth. The solar PV is one of the sources of renewable energy more suitable in Italy, thanks to a particularly favorable level of radiation.

The major problem related to the PV solar energy and the consequent scientific challenge is that its production greatly depends on the weather conditions of the area where the PV plant is installed. Prediction of the PV solar energy production for hours or days ahead can contribute to an efficient and economic use of this resource and can allow to manage the amount of energy obtained by PV plants in order to satisfy the growing demand of it. Furthermore, the increasing development of electrical smart grids has led to the need of knowing in advance the energy production from renewable sources in order to manage the energy flows within the smart grid itself: Forecasting the power output of a PV plant for the next hours or days is necessary for the optimal integration of this production into power systems.

There were many scientific investigations in this area carried out in recent years, and different forecasting strategies have been used to achieve the desired goals. In most cases, the studies have focused on the prediction of solar radiation, while there have been few articles devoted to the estimation of the production of PV solar energy. The

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state of art in this field is reported in [14]. The traditional prediction of PV energy production is based on the classical approach of time series forecasting of solar energy and weather conditions, which are used to calculate the electrical energy of PV systems: AutoRegressive models, Moving Average and Autoregressive Moving Averages [2] are often used to model linear dynamic structures. Furthermore, Fourier series models [3] can be used in order to predict the PV production. Another approach used to solve this problem is based on physical modeling. This approach seems to be less effective for complex nonlinear systems such as the forecast of irradiation fluctuation [1]. Moreover, different researches show that nonlinear and non-stationary models are more flexible in capturing the characteristics of these data and that, in some cases, are better in terms of estimation and forecasting. Many scientific articles [24] show that a predictive model based only on a database of historical data is expected to be more effective for the forecast of the energy production from a PV plant, because the influence of the specific system is somehow implicit in the past data. Nowadays, advanced models based on nonlinear approaches are rapidly spreading in the power production forecasting, using artificial neural network [6], support vector machines [7, 11] and hybrid models [17].

The aim of this work was to show how advanced machine learning techniques can be used for the prediction of PV energy generation in a real-world scenario. Specifically, the adopted approach utilizes Support Vector Machines for Regression. The goal was to obtain daily forecast for PV energy production with a quarter-hour frequency, as will be better explained in the next sections.

The paper is organized in the following way. The next section contains an explanation of support vector machine (SVM) for regression, then there is a section concerning the data used and the model implemented, and, at last, computational results, and final conclusions are pointed out.

We briefly describe our notation now. All vectors are column vectors and will be indicated with lower case Latin letter (x, z, ...). Subscripts indicate components of a vector, while superscripts are used to identify different vectors. The set of real numbers is denoted by $\mathbb{R}$. The space of the n—dimensional vector with real components will be indicated by $\mathbb{R}^n$. The symbol $||x||$ indicates the Euclidean norm of a vector x. Superscript ^{T} indicates transpose. The scalar product of two vectors x and y in $\mathbb{R}^n$ will be denoted by $x^T y$.

2 Support vector machines for regression

SVM is a new and promising nonparametric technique for data classification and regression [29], developed over the last fourth decades within the framework of statistical learning theory or VC theory (Vapnik–Chervonenkis Theory) [27, 28, 30]. The VC theory studies properties of learning machines, which enable them to well generalize to unseen data. SVMs were developed at AT&T Laboratories by Vapnik et al. and due to this industrial context, SV research has an orientation toward real-world applications [21, 25]. In this section, we briefly introduce the support vector regression (SVR), which can be used for time series prediction models, where excellent performances were obtained until now [8–10, 15, 16, 26].

Given training data $\{(x^1, y_1), \ldots, (x^l, y_l)\} \subset X \times \mathbb{R}$, where x^i are input vectors, $X \subseteq \mathbb{R}^n$ denotes the space of input patterns of dimension $\mathbb{R}^n$ and y_i are the associated output values for x^i, the goal in SVR is to determine a function $f(x)$ that has at most ε deviation from the set of target values y_i $(i = 1, \ldots, l)$ for all the training data and, at the same time, is as flat as possible. The SVR model [4] requires the solution of the following optimization problem:

$$\begin{aligned} &\min_{w,b,\xi,\xi^*} \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \\ &\text{subject to} \quad \mathrm{y_i} - (\mathrm{w}^T \phi(\mathrm{x}^i) + \mathrm{b}) \le \varepsilon + \xi_i^*, \\ &(w^T \phi(x^i) + b) - y_i \le \varepsilon + \xi_i, \\ &\xi_i, \xi_i^* \ge 0, \qquad i = 1, \ldots, l. \end{aligned} \tag{1}$$

where the vector x^i is mapped into a higher dimensional space by the function ϕ. The quantity ξ_i is an upper bound on the training error (and ξ_i^* is a lower bound) subject to the ε-insensitive tube

$$\left| y - (w^T \phi(x) + b) \right| \le \varepsilon. \tag{2}$$

The parameters which control the regression quality are the cost of error (C), the width of the tube (ε) and the mapping function (ϕ). The positive constant C determines the trade-off between the flatness of the function

$$f(x) = \sum_{i=1}^{l} w_i^T \phi(x^i) + b \tag{3}$$

and the amount up to which deviations larger than ε are tolerated. If the inequality (2) is not satisfied by x^i, there is an error ξ_i or ξ_i^* which the SVR model minimizes in the objective function. In fact, SVR avoids underfitting and overfitting of the training data by minimizing the training error $C \sum_{i=1}^{l} (\xi_i + \xi_i^*)$ as well as the regularization term $\frac{1}{2} w^T w = \frac{1}{2} \left\| w^2 \right\|$. For traditional least-square regression, the quantity ε is always zero, and data are not mapped into

Table 1 Examples of the principal kernel functions

Kernel function	Formulation
Linear	$k(x,y) = x^T Ay$
Polynomial	$k(x,y) = (x^T x + c)^d$
Radial basis function (RBF)	$k(x,y) = e^{-\gamma\|x-y\|^2}$

higher dimensional spaces. Hence, SVR is a more general and flexible tool for regression problems.

The use of the mapping function ϕ allows to take into account the fact that normally the function $f(x)$ that best fits the training data is nonlinear. Hence, the function ϕ is a way to make the SV model nonlinear. The function $\phi : \mathbb{R}^n \rightarrow H$ is a function mapping $\mathbb{R}^n$ into a higher-dimension Hilbert space H. In the dual formulation of problem (1), the *kernel function* is introduced

$$k(x^i, x) = \phi(x^i)^T \phi(x).$$

Examples of kernel functions are shown in Table 1. In recent years, several methods have been proposed to combine multiple kernels, instead of classical kernel-based algorithm using a single kernel [13]. These methods are known as Multiple Kernel Learning and Infinite Kernel Learning [12, 13, 20]. Nevertheless, in our study, we prefer to use a single kernel, as the literature suggests.

For the experiments in this paper, we use the open-source library LIBSVM [5] available for MATLAB. It enables using two different versions of SVR: the ε-SVR and the ν-SVR [4].

The version illustrated above is the ε-SVR, while the ν-SVM [4, 22, 23] problem is defined as follows:

$$\begin{aligned} \min_{w,b,\varepsilon,\xi,\xi^*} \quad & \frac{1}{2} w^T w + C\left(\nu\varepsilon + \frac{1}{l}\sum_{i=1}^{l}(\xi_i + \xi_i^*)\right) \\ \text{subject to} \quad & y_i - (w^T \phi(x^i) + b) \le \varepsilon + \xi_i^*, \\ & (w^T \phi(x^i) + b) - y_i \le \varepsilon + \xi_i, \\ & \xi_i, \xi_i^* \ge 0, \qquad i = 1, \ldots, l. \end{aligned} \tag{4}$$

Since it is difficult to select an appropriate ε, Schölkopf et al. [23] introduced the new parameter ν which allows to control the number of support vectors and training errors. To be more precise, ν is an upper bound on the fraction of margin errors, that is to say of training samples which are errors (badly predicted), and a lower bound of the fraction of support vectors: For regression, the parameter ν replaces ε and in our situation, it might be easier to use ν-SVR [4]. The main motivation for the ν version of SVR is that it has a more meaningful interpretation than ε: ε or ν are just different versions of the penalty parameter.

3 The photovoltaic energy production model

The aim of this paper was to predict the daily PV energy production. The work was carried out using historical data of an existing solar PV plant. These data were provided by the Loccioni Group (located in Angeli di Rosora, AN, Italy). A detailed study of the PV plant has been possible thanks to the availability of a large amount of recorded measurements, stored during the past years. Specifically, the data used are those related to the PV plant placed in their location in Angeli di Rosora, consisting of Solyndra panels, positioned on the roof of a building, with a nominal power of 112 kWp.

The collected measurements are energy and power produced by the plant, radiation (recorded directly by sensors placed on the roof, in the same position of the PV modules) and external environmental temperature. As the PV modules have a particular cylindrical shape, module temperature has little effect on their performance and it is not measured.

3.1 Data organization

In the previous section, we have briefly described the SVR model. Now we need to prepare the datasets used to build this model. In order to train the SVR model, we have to choose a diversified dataset of input vectors, representative of the real situation. Each component of the training data is called feature (or attribute). The first analysis consists on the selection of the necessary features of the input data.

Scientific researches have shown that there are many physical parameters, which PV production depends on: environmental temperature, solar irradiance, atmospheric pressure, wind speed, humidity and cloud coverage. However, many of these values are not available. For this reason, the model will consider in the training input data only the external temperature and the solar irradiance as features. Nevertheless, a preliminary study on the historical collected data has proved that the solar irradiance is the physical quantity mostly affecting the PV energy production. The scatterplot in Fig. 1 shows the correlation between the PV energy produced and the measured irradiance. The value of the Pearson correlation coefficient between the two measures is approximately 0.95, a high value suggesting a strong relationship between energy and irradiance. However, this strong relationship is not perfectly linear, in particular during the central hours of the day, and this is the reason why a model based on ν-SVR with a nonlinear kernel, as explained in the following section, is created for the energy production forecast.

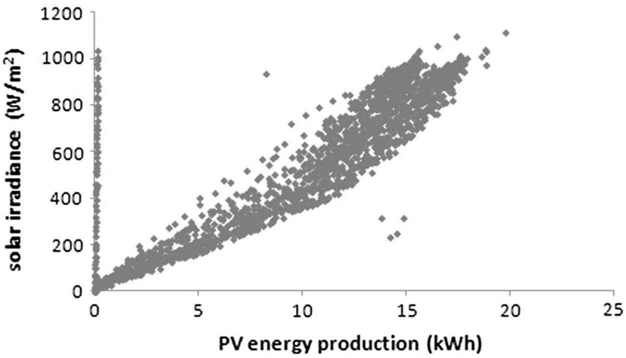


Fig. 1 The scatterplot of the correlation between solar irradiance and energy production from a PV plant

3.2 Model description

As discussed in the previous section, the training set of our ν-SVR model utilizes two different features (solar irradiance and environmental temperature), and hence, with reference to Sect. 2, $x^i \in \mathbb{R}^2$ and y_i are the energy production. The SVR model forecasts the energy production from the PV plant for the next day with a timestep interval of 15 min.

Upon the selection of the dataset for training, the SVM model is built to forecast energy production in the following time steps. First of all, the training data are scaled in the interval (0,1). Then, in training a SVM model, there are some parameters to choose, which would influence the performance of the ν-SVR algorithm. These parameters need to be properly selected in order to get a good model. They are

1. the cost of error C,
2. the kernel type and the constant appearing in the kernel formula,
3. the number of support vectors ν,
4. how many previous data to include for training.

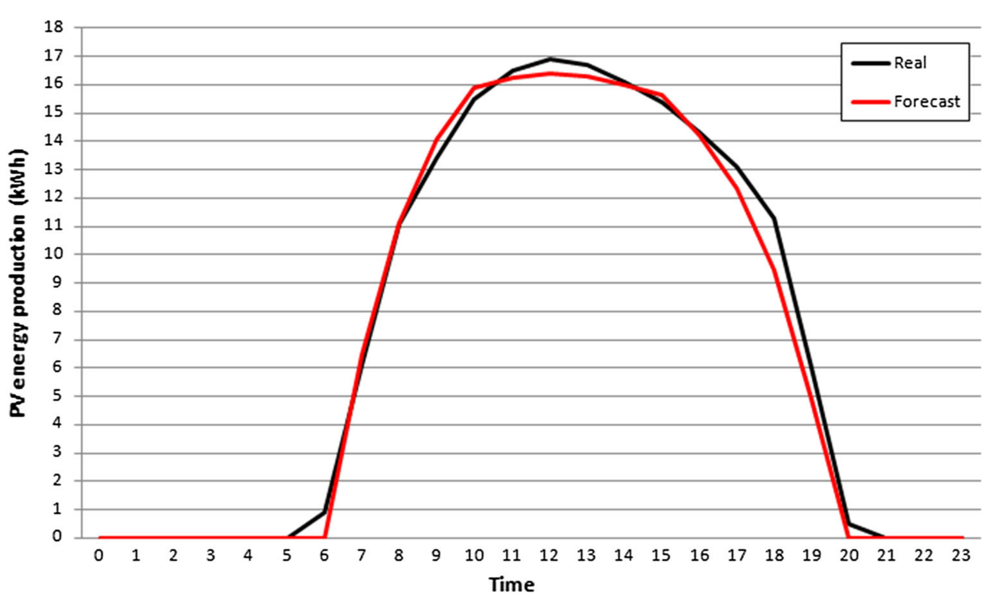
In our experiments, since we assume a daily prediction and since the algorithm will be retrained every night in order to obtain the energy production forecast for the next day, we simply include the irradiance, the temperature and the production data every 15 min of the previous 14 days as training set. In addition, we consider the radial basis function (RBF) as kernel function, which is one of the most commonly used mapping functions and the most commonly used for time series prediction. In this case, the parameter associated with the RBF kernel is γ and it has to be fine tuned. In our experiments, we fix γ to its default value. Also, we fix $\nu = 0.5$ which is again the default of LIBSVM [5]. The only parameter left is C. Searching the proper value of the cost of the error C is time-consuming and needs a great amount of experimental tests. After those tests, the value of C has been chosen equal to 1.8.

Once the SVR model is defined, we can use it to make prediction for the next day. The only inputs the algorithm needs to forecast are the estimated irradiance and environmental temperature for the next 24 h. In the following section, we show the results obtained with the new technique based on ν-SVR.

4 Computational results

In this section, we will report the computational results for three different days as obtained with the proposed SVR model. In our case of a real-world PV plant, the daily PV energy production was estimated from 00:00 to 23:45 with

Fig. 2 The plot of the PV energy production for June 15, 2012. In *black* the real values, in *red* the forecasted ones (color figure online)



steps of 15 min. Figure 2 plots the real and forecasted energy production values, for a sunny day in June 2012.

For the purpose of evaluating the quality of the forecasting, we examine the prediction accuracy by calculating three different evaluation statistics: the root mean square error (RMSE), the mean absolute percentage error (MAPE) and the coefficient of determination (R^2).

The RMSE, as in Eq. 5,

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (5)$$

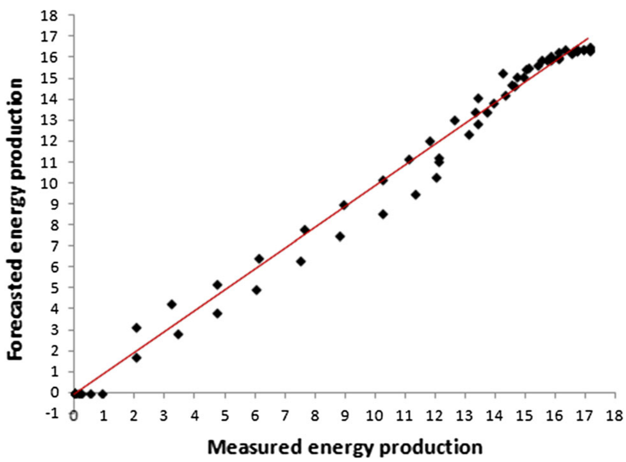


Fig. 3 The scatterplot of the correlation between real and forecasted energy production. The *red line* is the regression line (color figure online)

denotes the mean square discrepancy between the values of the observed data (y_i) and the estimated data ($\hat{y}_i$): The closer this value is to 0, the more accurate is the model.

The MAPE, defined in Eq. 6,

$$\mathrm{MAPE} = \frac{100\,\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (6)$$

is another measure of accuracy, to be interpreted in this way: In case of a perfect fit, its value is 0, while there are no restrictions with regard to the upper bound.

At last, the coefficient R^2, as in Eq. 7 where $\bar{y}$ indicates the mean of the actual data,

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (7)$$

is a proportion of the variability in the data and the correctness of the model used; R^2 varies in (0,1): It is 0 when the used model does not explain the data at all, it is 1 when the model explains the data perfectly.

In the first result, we obtain good values for the three measures of accuracy illustrated above:

- RMSE = 0.5275;
- MAPE = 0.0785;
- $R^2 = 0.9944$.

The quality of the prediction is confirmed by the scatterplot of the correlation between the measured energy production and forecasted values, as illustrated in Fig. 3.

Fig. 4 The plot of the PV energy production for April 16, 2012. In *black* the real values, in *red* the forecasted ones (color figure online)

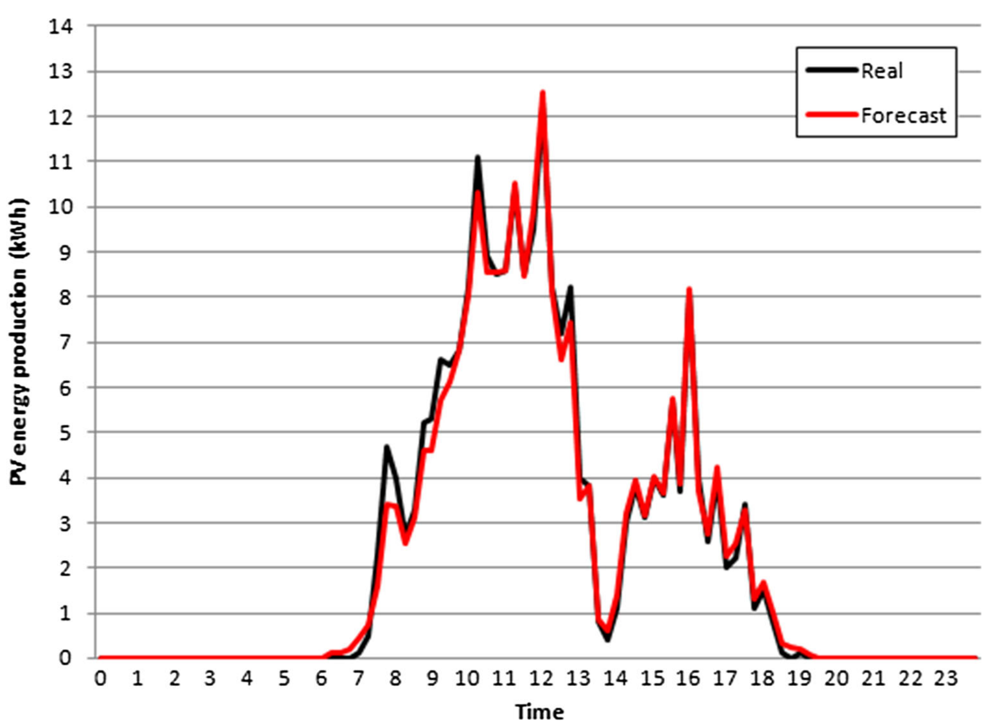
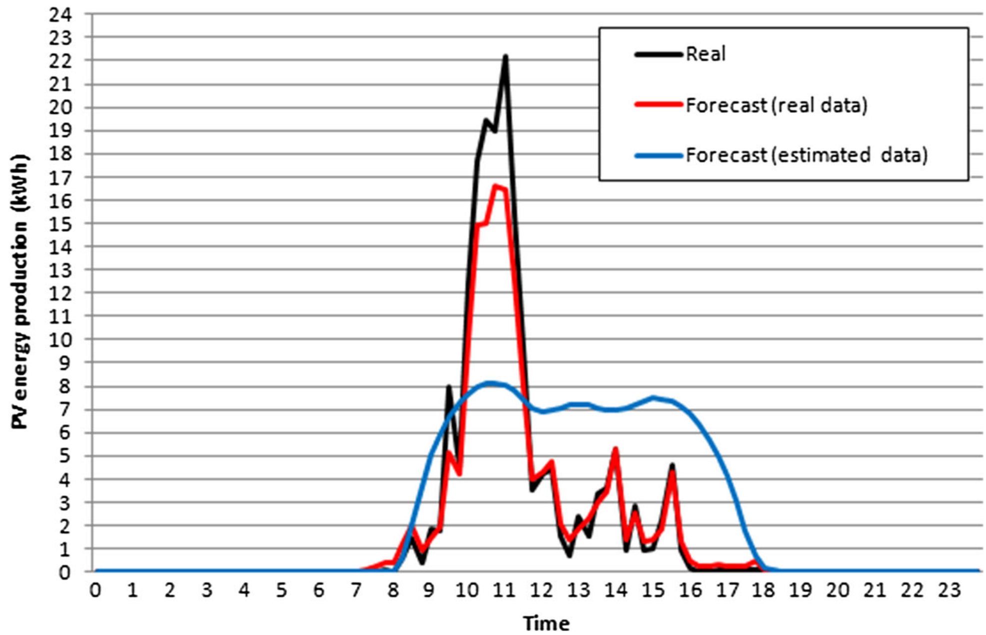


Fig. 5 The plot of the PV energy production for October 11, 2013. In *black* the real values, in *red* the forecasted ones using actual data of irradiance and temperature, in *blue* the prediction using estimated weather data (color figure online)



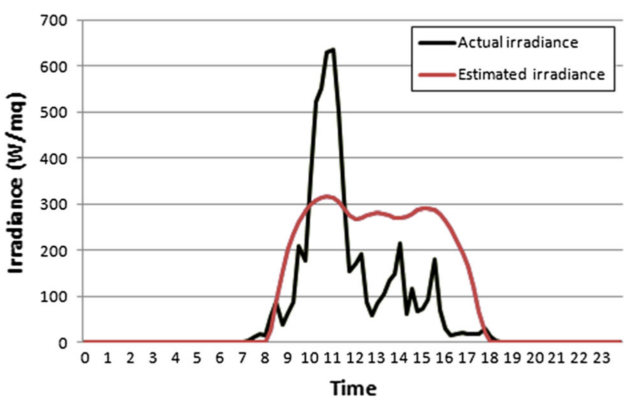


Fig. 6 The plot of the solar irradiance for October 11, 2013. In *black* the real values, in *red* the forecasted ones by the weather site (color figure online)

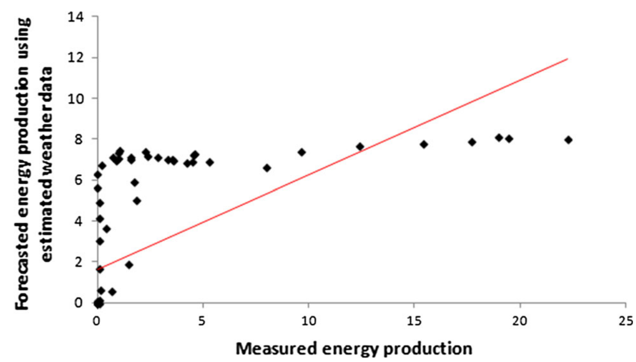


Fig. 7 The scatterplot of the correlation between real production and forecasted one obtained using estimated weather data. The *red line* is the regression line (color figure online)

Figure 4 plots the real and forecasted PV energy production values based on the ν-SVR model for a cloudy day in April 2012. The comparison between actual and predicted data shows an almost full agreement between both series. The accuracy measures prove this result: RMSE = 0.2810, MAPE = 0.1143 and $R^2 = 0.9926$.

Things are different when the input values of solar irradiance and environmental temperature for the next day are not fully accurate. Figure 5 shows this situation for a day in October 2013, where the forecasted irradiance provided by a weather site is far from reality, as pointed out in Fig. 6. The error made in the irradiance prediction is crucial for the forecast of the solar energy production. If the irradiance data used for the prediction were the measured ones, in fact, the production forecast would have good results: RMSE = 0.9955, MAPE = 0.3585 and $R^2 = 0.9508$. Instead, these measures get significantly worse if the solar irradiance and external temperature provided by the weather site are not accurate. In this case, the values of the three previous measures of goodness are, respectively RMSE = 3.5876, MAPE = 3.5718 and $R^2 = 0.3616$. Also, the scatterplot in Fig. 7 shows that the predicted values are far from the regression line. As we have observed before about the influence of irradiance in the PV energy production, the forecasted result follows the estimated error in the solar irradiance prediction. The presence of a correct irradiance is decisive for the energy prediction by the ν-SVR model. In fact, previous analysis show that the correlation between the two variables (irradiance and energy production) exceeds 95 %.

5 Conclusions

A new short-term energy forecasting model for PV plants, based on SVR, has been described in this paper. The aim of the model was to create a daily prediction of the PV energy production with values every 15 min. The main innovative characteristic of the model is the use of the ν-SVR, where we can tune the number of support vectors during the training of the algorithm.

The forecasting model of this paper has been tested using real-world data from a PV plant installed in Italy. The model takes into account the past energy production data and the historical measurements of irradiance and temperature. These values, provided by the Loccioni Group, show high intra-hour variability of the energy production output of the plant. This new forecasting model presents accurate results compared with the three different evaluation statistics explained above (RMSE, MAPE, R^2). The only risk of the forecasting model is associated with forecasting errors on input data (solar irradiance and environmental temperature) provided by weather internet sites.

6 Further works

Future researches will focus on the study of making the PV energy production forecast more robust, so that it does not depend so deeply from recorded solar irradiance, in order to use weather prediction provided by internet sites. One look will be directed to algorithms based on Infinite Kernel Learning [18, 19].

Furthermore, the study on energy production forecast can be inserted in the context of electrical smart grid. A smart grid is an electrical distribution network comprising various distributed power plants, storage devices and controllable loads: Knowing in advance the production from renewable sources present in the network allows to manage the energy flows within the smart grid itself, in order to satisfy the local demand, to achieve the goal of energy autonomy for the most of time and to ensure the maximum economic benefit.

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References

1. Aznarte J, Girard R, Espinar B, Moussa A, Kariniotakis G (2009) Forecasting functions with focus to PV prediction for microgrids. Tech. rep., project more microgrids. http://www.microgrids.eu/documents/639.pdf
2. Bacher P, Madsen H, Nielsen HA (2009) Online short-term solar power forecasting. Solar Energy 83(10):1772–1783
3. Bien T, Musikowski HD (2008) Forecasting photovoltaic energy using a fourier series based method. Engineering and system integration, pp 3088–3091
4. Chang CC, Lin CJ (2002) Training v -support vector regression: theory and algorithms. Neural Comput 14(8): 1959–1977 http://dblp.uni-trier.de/db/journals/neco/neco14.html#ChangL02
5. Chang CC, Lin CJ (2011) LIBSVM: A library for support vector machines. ACM Trans Intell Syst Technol 2: 1–27. Software http://www.csie.ntu.edu.tw/~cjlin/libsvm
6. Cococcioni M, D'Andrea E, Lazzerini B (2012) One day-ahead forecasting of energy production in solar photovoltaic installations: an empirical study. Intell Decis Technol 6(3):197–210. doi:10.3233/IDT-2012-0136
7. da Silva Fonseca J, Oozeki T, Takashima T, Koshimizu G, Uchida Y, Ogimoto K (2011) Photovoltaic power production forecasts with support vector regression: a study on the forecast horizon. In: Photovoltaic specialists conference (PVSC), 2011 37th IEEE, pp 2579–2583. doi:10.1109/PVSC.2011.6186475
8. De Cosmis S, De Leone R (2012) Support vector machine for robust regression. In: COMTESSA (ed) Proceedings of the CTW 2012 11th cologne-twente workshop on graph and combinatorial optimization, pp 96–99
9. De Leone R (2011) Support vector regression for time series analysis. In: Operations research proceedings 2010. Springer, Berlin, pp 33–38
10. Drucker H, Burges CJC, Kaufman L, Smola AJ, Vapnik V (1997) Support vector regression machines. In: Mozer MC, Jordan MI, Petsche T (eds) Advances in neural information processing systems 9. MIT Press, Cambridge, pp 155–161
11. Fonseca J Jr, Oozeki T, Takashima T, Koshimizu G, Uchida Y, Ogimoto K (2009) Forecast of power production of a photovoltaic power plant in japan with multilayer perceptron artificial neural networks and support vector machine. Large PV Power Plants and Distributed PV pp 4237–4240
12. Gehler P, Nowozin S (2008) Infinite kernel learning. Technical report 178, Max Planck Institute
13. Gönen M, Alpaydin E (2011) Multiple kernel learning algorithms. J Mach Learn Res 12: 2211–2268. http://dl.acm.org/citation.cfm?id=1953048.2021071
14. Jenkins N, Awad B, Ekanayake JB (2009) Advanced architectures and control concepts for MORE MICROGRIDS. Technical report, more microgrids project consortium
15. Mattera D, Haykin S (1999) Support vector machines for dynamic reconstruction of a chaotic system. In: Schölkopf B, Burges CJC, Smola AJ (eds) Advances in kernel methods. MIT Press, Cambridge, MA, USA, pp 211–241. http://dl.acm.org/citation.cfm?id=299094.299106
16. Müller K-R, Smola AJ, Rätsch G, Schölkopf B, Kohlmorgen J, Vapnik V (1997) Predicting time series with support vector machines. In: Gerstner W et al. (eds) Artificial neural networks—ICANN'97, vol 1327. Springer, Heidelberg, pp 999–1004
17. Ogliari E, Grimaccia F, Leva S, Mussetta M (2013) Hybrid predictive models for accurate forecasting in pv systems. Energies 6(4):1918–1929. doi:10.3390/en6041918http://www.mdpi.com/1996-1073/6/4/1918
18. Özögür-Akyüz S, Weber GW (2010) Infinite kernel learning via infinite and semi-infinite programming. Optim Methods Softw 25:937–970. doi:10.1080/10556780903483349
19. Özögür-Akyüz S, Weber GW (2010) On numerical optimization theory of infinite kernel learning. J Glob Optim 48(2):215–239. doi:10.1007/s10898-009-9488-x

20. Özögür-Akyüz S, Ünay D, Smola AJ (2011) Guest editorial: model selection and optimization in machine learning. Mach Learn 85(1–2):1–2
21. Pellegrini M, De Leone R, Maponi P (2013) Reducing power consumption in hydrometric level sensor network using support vector machines. In: PECCS (ed) Proceedings of the PECCS 2013 international conference on pervasive and embedded computing and communication systems, pp 229–232
22. Schölkopf B, Bartlett P, Smola A, Williamson RC (1999) Shrinking the tube: a new support vector regression algorithm. In: Kearns MS, Solla SA, Cohn DA (eds) Advances in neural information processing systems 11. MIT Press, Cambridge, pp 330–336
23. Schölkopf B, Smola AJ, Williamson RC, Bartlett PL (2000) New support vector algorithms. Neural Comput 12(5):1207–1245. doi:10.1162/089976600300015565
24. Simonov M, Mussetta M, Grimaccia F, Leva S, Zich R (2012) Artificial intelligence forecast of pv plant production for integration in smart energy systems. Int Rev Electr Eng 7:3454–3460
25. Smola AJ, Schölkopf B (2004) A tutorial on support vector regression. Stat Comput 14(3):199–222. doi:10.1023/B:STCO.0000035301.49549.88
26. Stitson M, Gammerman A, Vapnik V, Vovk V, Watkins C, Weston J (1997) Support Vector regression with ANOVA decomposition kernels. http://citeseer.nj.nec.com/stitson97support.html
27. Vapnik V (1982) Estimation of dependences based on empirical data. Springer Series in Statistics, Springer, New York
28. Vapnik VN (1995) The nature of statistical learning theory. Springer, New York
29. Vapnik V (1998) Statistical learning theory. Wiley, New York
30. Vapnik V, Chervonenkis A (1964) A note on one class of perceptrons. Automation and remote control 25