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Short-term forecasting model for electric power production of small-hydro power plants

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ABSTRACT

This paper presents an original short-term forecasting model for hourly average electric power production of small-hydro power plants (SHPPs). The model consists of three modules: the first one gives an estimation of the "daily average" power production; the second one provides the final forecast of the hourly average power production taking into account operation strategies of the SHPPs; and the third one allows a dynamic adjustment of the first module estimation by assimilating recent historical production data. The model uses, as inputs, forecasted precipitation values from Numerical Weather Prediction tools and past recorded values of hourly electric power production in the SHPPs. The structure of the model avoids crossed-influences between the adjustments of such model due to meteorological effects and those due to the operation strategies of the SHPPs. The forecast horizon of the proposed model is seven days, which allows the use of the final forecast of the power production in Power System operations, in electricity markets, and in maintenance scheduling of SHPPs. The model has been applied in the forecasting of the aggregated hourly average power production for a real-life set of 130 SHPPs in Portugal achieving satisfactory results, maintaining the forecasting errors delimited in a narrow band with low values.

1. Introduction

The knowledge of the temporal evolution of electric load and power production is important for technical operations and control of Power Systems, because electric demands must meet, at all times, secure and reliable operation. Furthermore, the electric power production scheduling for the next days (i.e., next seven days, or even more) is related to the economic operation of the Power System in a context of electricity markets. Such power production also affects power plants maintenance.

Power System operation, at the moment, faces new challenges associated with non-controlled power independent producers, such as wind farms, photovoltaic plants and small-hydro power plants (SHPPs). At the moment, a large amount of the independent renewable power generation is characterized for being a type of electric power production difficult to control: thus, on one hand, generally there is some kind of intermittency in the power resource, which is not controllable, while on the other hand, there are as many operation strategies as managers of renewable power stations. Furthermore, these strategies can be influenced through price signals or general technical restrictions, but they are based on the individual decision of each independent renewable power producer.

Short-term forecasting of power production, for each kind of renewable power plant, is a key matter for the Power System, since such short-term forecasting is an essential tool for ensuring power supply, planning of reserve plants, or inter-power-systems electric energy transactions, or helping to solve power network congestion problems. For the renewable power producer, short-term forecasting is crucial for playing in the electricity market or scheduling maintenance tasks.

A lot of research activity has been carried out, during the last years, in the short-term forecasting of wind power production. The development of Numerical Weather Prediction (NWP) models, which offer forecasts of weather variables for the next days, has helped in the improvement of short-term wind forecasting models based on physical models or statistical models [1]. In the photovoltaic field, some works have been published describing short-term photovoltaic production models, most of them based on the forecast of incident solar radiation [2].

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Most of the published short-term forecasting models related to hydro power matters are used for water management through the forecasting of inflow in reservoirs [3–5], of streamflow [6,7], or of precipitation [8]. Neural networks are the most applied technique for these short-term forecasting models [9]. Forecasting models have been also applied to estimate the capacity of a mini-hydro power plant [10], generation scheduling of a micro-hydro power plant [11], and monthly ideal generation of a large hydro power plant [12], but there is no research work referring to the short-term hourly electric power production forecasting for SHPPs.

This paper presents a novel short-term forecasting model (named H4C) for hourly average electric power production of SHPPs for the next seven days. The H4C uses, as input variables, past values of recorded electric power production in the SHPPs as well as forecasted values of precipitation (from an NWP tool). Such model takes into account control strategies of the small-hydro power plants, according to paying tariff for the electric energy production. The forecasted values from the H4C can be used by managers of SHPPs for economic bids in electricity markets and maintenance scheduling of plants, and by the Power System Operator for technical purposes.

The paper is structured as follows: in Section 2, the new forecasting model H4C for SHPPs is described; a real-life case study, with the application of the H4C to the forecast of the aggregated hourly average power production of a set of SHPPs, is presented in Section 3; finally, the conclusions are included in Section 4, showing the advantages offered by the H4C. The results achieved by the proposed model significantly improve those obtained with the persistence forecasting model.

2. Proposed forecasting model

The proposed forecasting model, H4C, is composed of three modules:

- The first one is used to estimate the daily average power production (kW) of the small-hydro power plants (SHPPs) using precipitation values forecasted by meteorological NWP models. Through the paper we will assume as “daily average” the “moving average”, centered in hour t. However, other definitions of “daily average” could be used to apply the model maintaining the efficacy of the application of such model. For instance, also a daily average value, between $t-23$ and t could be assumed.
- The second module takes into account the operation strategy of the SHPPs. It estimates the hourly pattern of the electric power production, detailing for each hour of the day the hourly average power generation (kW), i.e. electric energy produced in such hour, using the daily average power production forecasted by the previous module.
- There exists also an assimilation module that complements the two previous modules, used to adjust the BIAS error of the daily average power production to the real production.

The three modules are described in detail in the next paragraphs. In order get a better understanding of the mathematical and methodological description of the model, a case study is included corresponding to the forecasts of the aggregated power generation of all the SHPPs in Portugal (130 SHPPs, with a capacity lower than 10 MW each, totalizing 350 MW). However, the same methodology can be applied efficiently for one SHPP individually.

2.1. First module: daily average electric power production

The electric power production in SHPPs is naturally related to the water flow and, consequently, related to the precipitation in the drainage basins where the SHPPs are located. This relationship is visually evident in Fig. 1; however it cannot be easily and directly established by mathematical regression between precipitation and electric power production. In Fig. 1, the vertical axis represents the hourly average power production (recorded production) for the aggregation of the SHPPs (kW), and the forecasted hourly average precipitation per hour (mm). These forecasted average precipitation values were obtained from NWP weather forecasting services.

Some of the reasons that make it difficult to relate the precipitation and the electrical production in SHPPs include the following:

- Forecasted values of hourly average precipitation present frequently phase-shift errors (temporal deviation between the expected and real moment of the precipitation). The error, with average values on a daily basis, is lower than those on an hourly basis.
- There is a delay between the instant that the precipitation occurs and the instant that the hydro-resource arrives to the SHPPs reservoirs. This delay depends on the terrain characteristics. For a “daily average” approach this detail loses relevance.
- The electric energy production is mainly influenced by the operation strategy of the SHPPs, being the hourly timing for generation practically independent of the hourly timing of the precipitation.

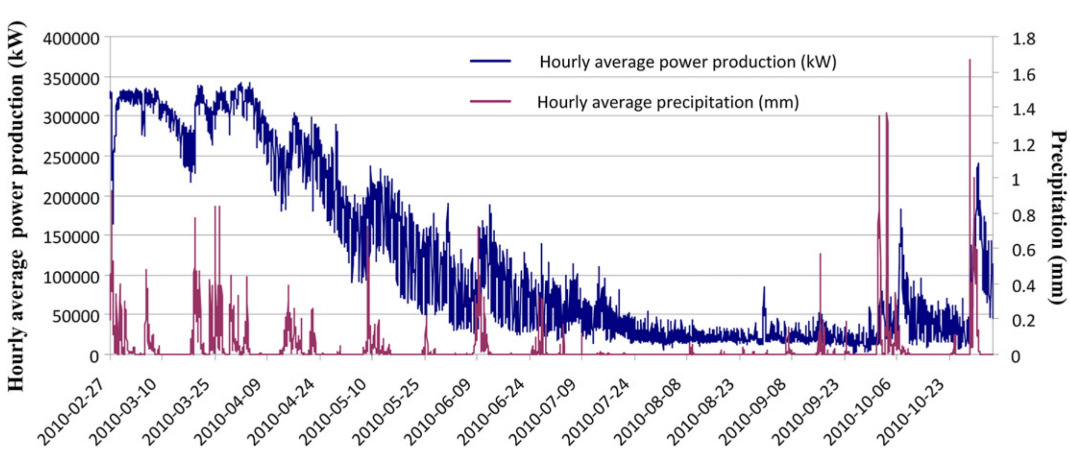

Fig. 1. Hourly average power production and hourly average precipitation.

These reasons suggest the use of daily average (in the above-mentioned sense) values for the electric power production and for the precipitation, which leads to a clearer relationship between both variables, as shown in Fig. 2. In such Fig. 2, the daily average electric power production follows the variations of the daily average forecasted precipitation, with a fast increase in production for days with precipitation, while such production decreases slightly in dry periods.

In order to establish a mathematical relationship between the daily average values of forecasted precipitation and those of power production, we define a new variable, named the Hydrological Power Potential (HPP). This variable HPP represents the level of hydrological potential to produce electrical power. In the approach used in this paper, the HPP is a daily average value that depends on the daily average forecasted precipitation. Equation (1) defines the HPP value for the hour h of the day d.

$$H_{d,h} = B(H_{d-1,h} + A \cdot R_{d,h}) \tag{1}$$

where

- $H_{d,h}$ is the HPP for the hour h of the day d, in kW.
- $H_{d-1,h}$ is the HPP for the hour h of the day $d-1$, in kW
- A is the parameter related to the incremental response of the electric power generation to the precipitation, in kW/mm.
- B is the dimensionless parameter that is related to the speed of decrease of such generation in dry days. This parameter has values lower than 1.
- $R_{d,h}$ is the daily average forecasted precipitation for hour h of the day d, in mm.

Forecasted precipitation, to be used in Equation (1) applied to a set of SHPPs, is calculated as a weighted value of forecasted local precipitations in locations near such SHPPs, using their rated powers as weights.

Fig. 3 shows the temporal evolution of the daily average real power aggregated production in a set of SHPPs and its HPP. The increase in the daily average power production (in kW) occurs for rainy days, with an increment proportional to the precipitation (in mm). The slope of this proportion is characterized by the parameter A, while the parameter B represents the decrease in the daily average power production in dry days. Both A and B parameters are obtained by the least squares error method, taking as error the difference between the daily average recorded power production value and the corresponding HPP value. The adjustment for parameter A can be noticed in Fig. 3, in the periods with an increase in the production, which coincide with the rainy days.

In Fig. 3, the matching between the evolution of HPP and the daily average of the recorded electric power production is not perfect because there are non-linearities that are associated with the minimum and maximum power generation of the SHPPs. Thus, a sigmoid mathematical curve is used for converting the hydrological power potential, $H_{d,h}$, in power production, as described in the following paragraphs.

Fig. 4 shows a scatter plot of the point cases ($H_{d,h}$, $P_{record\_d,h}$), where $P_{record\_d,h}$ represents the daily average recorded electric power production for the hour h of the day d, which is represented in vertical axis (kW), and $H_{d,h}$ is represented in horizontal axis (kW). A sigmoid curve can be adjusted to such set of points. It allows the obtaining of an estimated daily average electric power production, $P_{est\_d,h}$ as a function of $H_{d,h}$. This sigmoidal shape takes into account the technical limitations of the SHPPs: a minimum saturation value of $P_{est\_d,h}$ corresponds to the minimum value of $H_{d,h}$, and a maximum saturation value of $P_{est\_d,h}$ corresponds to the maximum value of $H_{d,h}$. Notice that all the variables are hourly average for a 24 h moving window (daily average values).

So, the estimated daily average electric power production value can be calculated by (2), where $P_{est\_d,h}$ corresponds to such production value for the hour h of the day d; P_{min} is the minimum power production value for the SHPPs; P_{max} is the maximum power production value for the SHPPs; and h_c and h_s are two parameters needed in the adjustment. These two parameters are defined in (3), where h_m and h_0 represent the HPP values where the sigmoid curve reaches the maximum and minimum saturation levels, respectively (P_{max} and P_{min}). Observe that all variables ($H_{d,h}$, P_{min}, P_{max}, $P_{est\_d,h}$) and parameters (h_c, h_s, h_m, h_0) are expressed in kW.

$$P_{est\_d,h} = P_{min} + \frac{P_{max} - P_{min}}{\left(1 + e^{\left(-8\frac{H_{d,h}-h_c}{h_s}\right)}\right)} \tag{2}$$

$$\begin{cases} h_c = \dfrac{h_0 + h_m}{2} \\ h_s = h_m - h_0 \end{cases} \tag{3}$$

Fig. 5 plots, in the vertical axis, the evolution of the daily average recorded power production value and its estimated value. With respect to Fig. 3, a better adjustment of such estimated power to that daily average recorded power production can now be observed.

Finally, with the first module completely parameterized, it can be applied in forecasting operation mode. The operational application of such first module corresponds to the following steps:

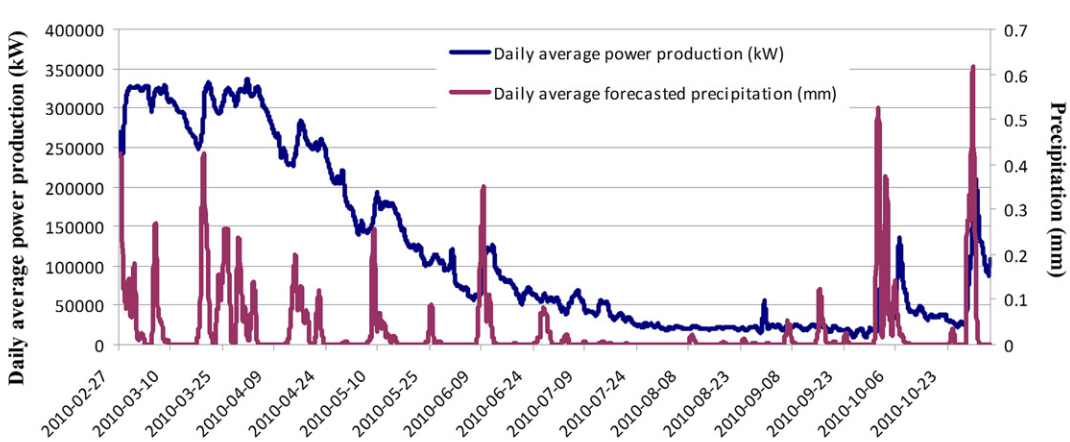

Fig. 2. Daily average power production and daily average forecasted precipitation.

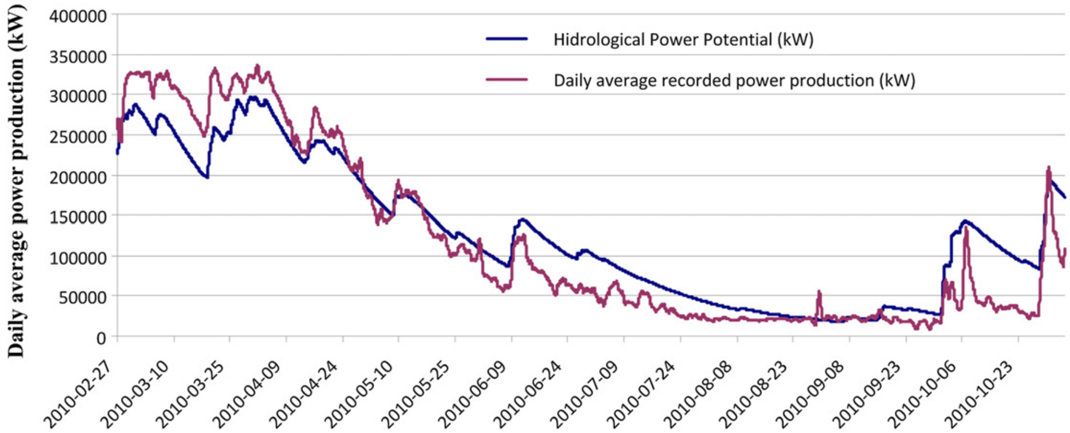

Fig. 3. HPP and daily average recorded power production.

1. From meteorological NWP services, to obtain forecasted precipitation values, for the next seven days.
2. To compute a 24 h moving average of the hourly forecasted values of precipitation, in order to obtain the daily average precipitation.
3. To compute the hydrological power potential $H_{d,h}$, with equation (1).
4. To compute the estimated daily average power production $P_{est\_d,h}$, with equation (2).

2.2. Second module: hourly average electric power production

In this subsection we describe the basic ideas referred to the operation strategies of SHPPs and the methodology employed in the modeling of such strategies. Usually, the operation strategy of an SHPP differs from case to case. The differences are reflected in the daily variability pattern of the electrical production. When the HPP associated to an SHPP presents a high value, such SHPP produces the maximum power value during all the time; when the HPP presents a low value, the SHPP produces only during a few hours per day, or with a low power value during all the day. With intermediate values of HPP, the SHPP follows the most interesting strategy of the manager, under an economic standpoint.

So, there are several typical strategy options in the operation of an SHPP according to the paying tariff for the electric energy production:

1. Constant tariff scheme throughout the whole day. In this case, with no economic incentives to generate electric power in certain hours, the SHPP will produce with the maximum possible technical efficiency at all times, and will stop when the water flow is insufficient for an efficient operation.
2. Double tariff scheme with high tariff values for load peak and flat hours and lower tariff value in load valley hours. The operation strategy is to produce the maximum possible of electric power for load peak and flat hours, and to produce electric power in load valley hours, only if the water flow is sufficient for an efficient operation.
3. Dynamic tariff scheme. In this case the incomes are linked to the electricity market prices. The operation strategy is based on an economic optimization of the electric power production, with greater production for the hours with a higher market price.

The approach, presented in this paper, for hourly average power forecast (second module) is designed for the cases of constant or double tariff schemes. For the case of dynamic tariff, the hourly average power forecast requires a different approach based on SHPP dispatch optimization, beyond the scope of this paper.

Knowing the estimated daily average power production, computed by the methodology presented in the previous section (first module), an Artificial Neural Network (ANN) is used to learn the pattern of the recorded hourly electric power production. Following training in the ANN, the hourly average power production forecasting can be obtained. For this purpose we used a specific type of ANN: a multilayer perceptron (MLP). For the real-life example (case study) presented later in this paper, corresponding to a set of SHPPs with double tariff scheme, the selected MLP is composed of one hidden layer with 27 neurons, three inputs and 24

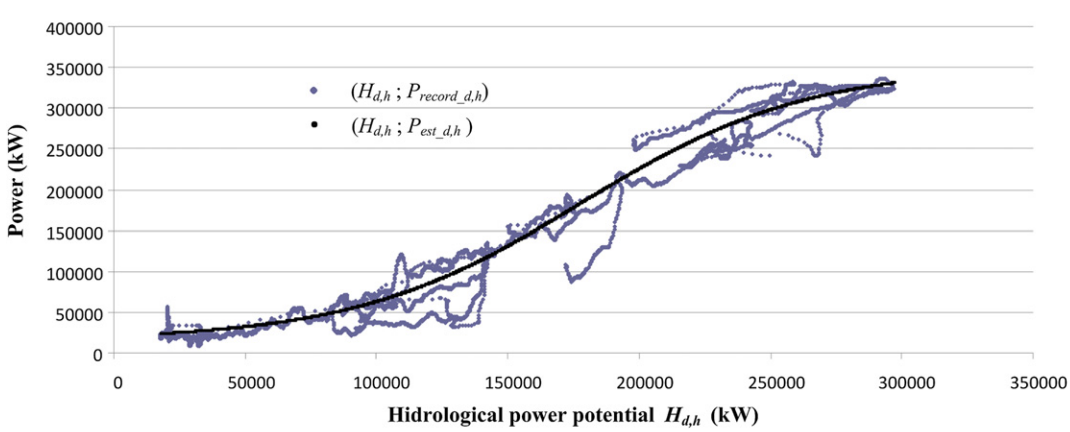

Fig. 4. Scatter plot and parametrized sigmoid.

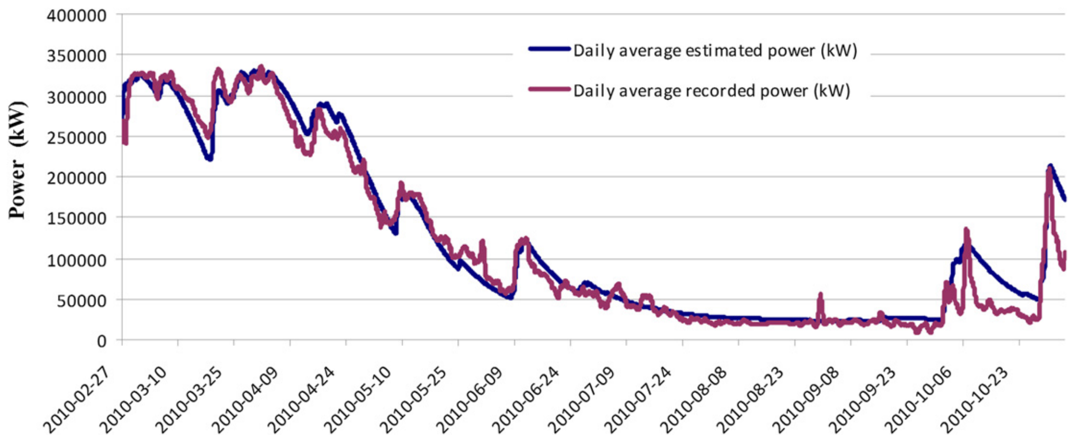

Fig. 5. Estimated daily average power and daily average recorded power.

outputs. The number of neurons in the said hidden layer was chosen on a trial and error basis. The MLP provides the hourly average power production for the following 24 h to an instant t (24 outputs with the production values for hours from t to $t+23$). The first input of the MLP corresponds to the estimated daily average power production forecast for instant $t+12$ (this input was obtained from the first module); and the other two inputs are x_1 and x_2, given in (4), where h is the hour of the day, from 0 to 23, corresponding to instant t.

$$\begin{aligned} x_1 &= \sin\left(\frac{h}{24}2\pi\right) \\ x_2 &= \cos\left(\frac{h}{24}2\pi\right) \end{aligned} \tag{4}$$

The MLP is able to learn the hourly electric production pattern of the SHPPs, which depends on the Hydrological Power Potential (HPP). For a high HPP value, the MLP does not distinguish the level of power production between high and low tariff periods and the output, corresponding to the hourly average power production forecasting, reaches a maximum value independently of the hour of the day. If the HPP value is low, the MLP learns a pattern with greater production in hours corresponding to the high tariff, and lower production in the hours with a low tariff.

Fig. 6 shows an example of the hourly power production in a set of SHPPs and the corresponding estimation of the daily average power production value, which is the first input variable of the MLP.

2.3. Third module: BIAS error adjustment based on recorded electric power production data assimilation

The model, H4C, described in the previous subsections, can be affected by a BIAS error, because the errors in the daily average forecasted precipitation values can imply significant deviations in the HPP values. Such deviations can be propagated over time, making the forecasting errors significant in the following days. The correction of the HPP values allows reducing forecasting errors in the final hourly average power production. The correction can be used with suitable frequency, according to the data availability in each case.

The BIAS error adjustment of the model H4C is made on the value of the HPP when there are significant differences between the daily average power production forecasts and the daily average recorded

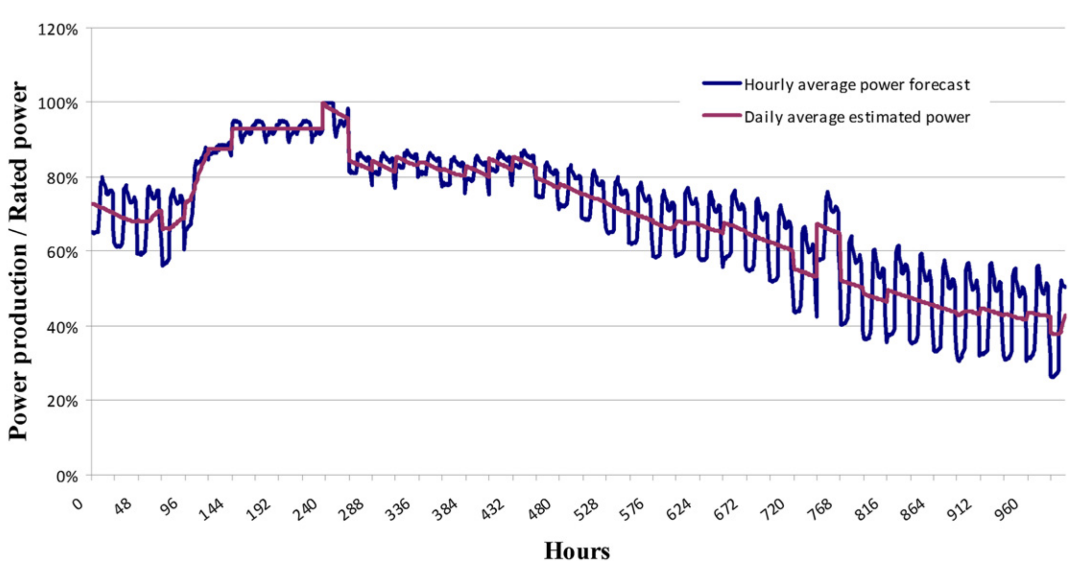

Fig. 6. Hourly average power forecast and estimated daily average power forecast.

electric power production values. The BIAS adjustment is carried out using equation (5), where $H_{aj\_d,h}$ corresponds to the hydrological power potential adjusted value for hour h and the day d.

$$H_{aj\_d,h} = h_c - \frac{h_s}{8}\ln\left(\frac{1}{P_{record\_d,h} - P_{min}}(P_{max} - P_{min}) - 1\right) \quad (5)$$

The BIAS adjustment process can be applied in any instant, allowing improvements in the forecasting of errors. For illustrative purposes, Fig. 7 shows the daily average recorded power production in the set of SHPPs, and the corresponding estimated daily average power production values, with and without the BIAS correction in the value of the HPP on a weekly basis.

3. Case study for aggregated electric power generation forecast of small hydro power plants

The forecasting methodology described in this paper (model H4C) was implemented into a new forecasting system belonging to a European specialized forecasting enterprise, and applied to a set of 130 SHPPs in Portugal with a total capacity of 350 MW. All these SHPPs sell the produced electric energy under a double tariff scheme, with near 0.09€ per kWh for the energy produced between 08:00 and 23:00, and a lower price (near 0.07€ per kWh) for the energy produced during the remaining hours. Such tariff scheme has an impact on the strategy of electric energy production in almost 40% of the set of studied SHPPs.

The precipitation forecasts were obtained with an NWP tool, the WRF model [13] using a spatial resolution of 5 km, providing the values for 150 geographical points placed near the SHPPs under study. With the precipitation forecasts and for each forecasting day (up to one week ahead), the daily average of weighted precipitation values was calculated; the weighting factors were selected according the rated power of each SHPP. This process was carried out 4 times per day. The forecasts produced at 00:00 h are used in this case study.

As above mentioned, the forecasting model H4C was applied in order to obtain the aggregate electric power production forecasts of the set of SHPPs using the precipitation forecasts and the last aggregated real electric power production values, which are available with a three days' delay. The BIAS adjustment was carried out as soon as new aggregated real electric power production data were available.

Fig. 8 shows the hourly average real power production in the set of SHPPs and the hourly forecasted values by the model H4C that correspond to the forecasts for the following day (day $D + 1$ if forecasts are produced at 00:00 of the day D). In the middle of the period, represented in Fig. 8, there was a week with high precipitation values, what caused an increase in the average electric production from near 150 MW to the maximum value of 350 MW. After that week, electric production decreased gradually. The values forecasted by the model H4C presents a daily pattern of hourly average electric power close to the real values, as a consequence of the effect of the double tariff. This daily pattern is hardly perceivable when there is a high hydrological power potential value.

Furthermore, an error analysis was carried out with the forecasts corresponding to a test period (days between 01/01/2011 and 03/07/2011). The forecasts used were those obtained at 00:00 h and correspond to the aggregated electric power production in the studied set of SHPPs. In such error analysis the percentage error (PE), the mean deviation of the forecasts (BIAS), and the mean absolute percentage error (MAPE) were calculated. Equation (6) defines the percentage error, equation (7) defines the BIAS, and equation (8) defines the MAPE. In equations (6)–(8), for hour t, PE_t is the percentage error, P_{real_t} is the real hourly average electric power value, $P_{forecast\_t}$ is the final forecasted hourly average electric power value; and BIAS is the mean deviation expressed in percentage (BIAS error), N is the number of hours in the test period, and MAPE the mean absolute percentage error.

$$PE_t = \frac{P_{real\_t} - P_{forecast\_t}}{P_{real\_t}}100 \quad (6)$$

$$BIAS = \frac{1}{N}\sum_{t=1}^{N}\frac{P_{real\_t} - P_{forecast\_t}}{P_{real\_t}}100 \quad (7)$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|P_{real\_t} - P_{forecast\_t}\right|}{P_{real\_t}}100 \quad (8)$$

Fig. 9 shows the histogram of the percentage errors in the test period (intervals of PE values are represented in the horizontal axis; while the percentage of the total cases, that is hours, corresponding to such values of PE_t are represented in the vertical axis). In Fig. 9 it can be observed that there is not a perfect symmetry, with forecasting errors by excess of greater magnitude, and more frequent small forecasting errors by defect.

Table 1 shows the BIAS error and the MAPE for the model H4C and for the persistence model corresponding to the test period. In the persistence model, the forecast is equal to the last known value,

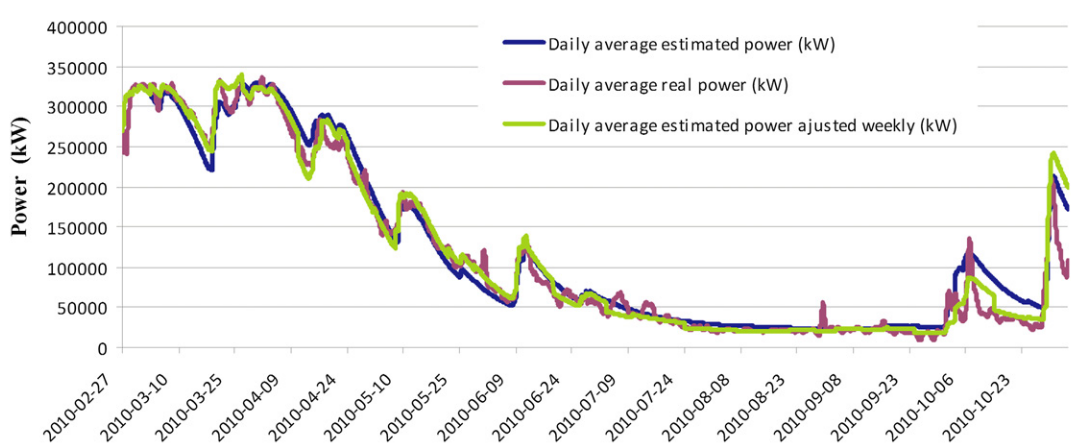

Fig. 7. Estimated daily average power production, daily average recorded power production and estimated daily average power production with the HPP adjusted weekly.

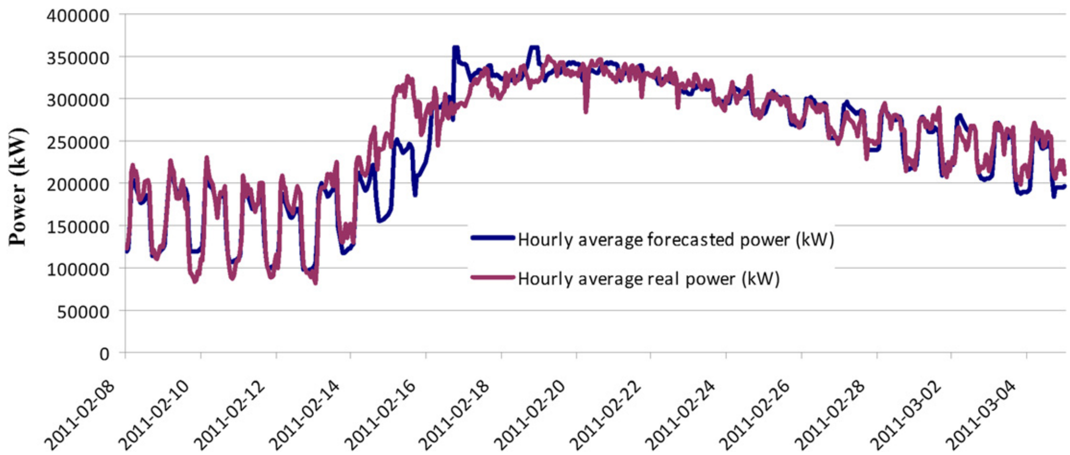

Fig. 8. Hourly real electric power values and forecasted values.

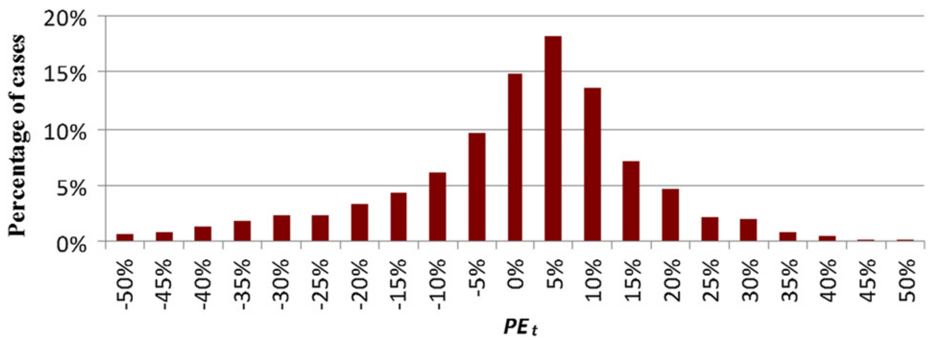

Fig. 9. Histogram of the percentage error, PE_t.

so, in this case, the forecast of the aggregated hourly average power production value for the hour h of the day $D+k$ (k ranges from 0 to 6, and the forecasts are carried out at 00:00 h of the day D) is equal to the real average power production value for the hour h of the day $D-3$.

As shown in Table 1, the forecasting errors for the model H4C increase slightly with the forecasting horizon, growing the MAPE from 11.9% (day D) to 18% (day $D+6$). In addition the BIAS error for the model H4C stays delimited between −3% and −3.8%, whereas the persistence model has BIAS error between −5.3% (day D) and −18.2% (day $D+6$). The BIAS error for the model H4C, error by excess, is due to the asymmetry of the distribution of the error (shown in Fig. 9), which is a characteristic of the forecast of the hydroelectric production. For the seven days included in the forecasting horizon (from D to $D+6$), the model H4C improves the MAPE value in a 38% and the BIAS value in a 69% with respect to the persistence model.

Table 1
BIAS error and MAPE values for the H4C and persistence models.

	Model H4C		Persistence ($D-3$)	
	BIAS	MAPE	BIAS	MAPE
D	−3.0%	11.9%	−5.3%	16.6%
$D+1$	−3.3%	12.8%	−7.5%	19.6%
$D+2$	−3.6%	13.7%	−9.8%	22.1%
$D+3$	−3.7%	14.3%	−11.9%	24.0%
$D+4$	−3.8%	15.5%	−13.7%	25.5%
$D+5$	−3.7%	16.5%	−15.7%	27.4%
$D+6$	−3.6%	18.0%	−18.2%	30.4%

4. Conclusions

This paper presents an original model, H4C, which integrates a novel methodology for the short-term forecasting of the hourly average electric power production in SHPPs. The model H4C offers practical solutions for some of the technical and economic problems caused by the variable generation of this kind of power plant.

The forecast of the power production in SHPPs is needed for the proper operation of the Power System, for preparing bid offers in the electricity markets, and for the maintenance scheduling of these power plants. The Power System Operator needs to know in advance the variability in the hydro power production, especially if this production can experience significant ramps (increase or decrease greater than the 40% of the rated power) in very short periods (less than half an hour). These production ramps are due to the tariff schemes used in the electric energy production. On the other hand, the bid offers to the electricity market, from other producers, can depend on the intermittency in the SHPPs production.

The new statistical model proposed in this paper, H4C, uses forecasted precipitation values obtained with an NWP tool, and utilizes them in the forecasting of the hourly average power production in SHPPs. One of the main innovations in the model H4C is the representation of the available hydraulic resource, by using an original index, that is, the hydrological power potential, HPP, which includes the inertia of the hydro-resource. This approach allows the modeling of the electric power production, with increases in the periods with precipitation, and decreases in dry periods.

The model H4C comprises three modules. The first module provides a forecast of the daily average electric power production in the SHPPs, which depends on the precipitation forecast and the HPP values. The second module gives hourly average power forecasts, which depend on the operation strategy of the SHPPs and the economic remuneration of the electric energy production. The separation between the meteorological effects and those due to the operation strategy of the SHPPs, is another innovation described in the paper: this separation carries an important advantage, in that it avoids crossed-influences between the adjustments of the model due to meteorology (first module for the daily forecast), and the adjustments due to the operation strategy of the SHPPs (second module for hourly forecasts).

The third module of the model H4C incorporates a suitable procedure for real information assimilation, which greatly improves the BIAS error of the forecasts carried out by the first module. This data assimilation procedure is possible thanks to the new index HPP mentioned above. Such procedure can be applied periodically (weekly or monthly) or applied with the frequency selected by the user.

The model H4C can be used for a set of SHPPs, providing its aggregated hourly average electric power production forecasts, or for a single SHPP, providing its hourly power production forecasts. The performance of such model H4C has been tested with data corresponding to a set of real-life SHPPs in Portugal (130 plants). In the case study described in this paper, the model H4C provided the aggregated hourly average power production with a total forecasting horizon of seven days. Thus, the forecasting results show significant improvements with respect to those obtained with the persistence model. The forecasting error, with the model H4C, increases very slightly with the forecasting horizon, maintaining the BIAS error delimited in a narrow band with low values.

Furthermore, the model H4C has been implemented in a European forecasting enterprise that offers real-life services to industrial customers. Indeed, the case study included in this paper refers to a real case within the scope of the mentioned services.

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