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VARIABILTY OF LONG TERM ESTIMATES OF HYDRO POWER GENERATION ON A EUROPEAN SCALE

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ABSTRACT

Hydro power production strictly depends on the geography and weather peculiarity of locations where power plants are settled. In this paper, we produce long term estimates of hydro power capacity factors for all European countries based on future climate scenarios. We use machine learning techniques for formalizing models able to capture the complex relation between climate variables and energy production on a European scale and use the results of regional and global climate models for future projections.

Keywords: Energy modeling; machine learning; hydropower generation; energy and climate systems.

1. INTRODUCTION

Hydro power (HP) is the world's most dominant (86%) source of renewable electrical energy. Installed hydro power capacity continues to grow quickly with the aim at decreasing carbon-based or nuclear power generation. During 2017, an additional 21.9 GW of installed hydropower capacity was added worldwide (2.3 GW in Europe) [1]. Table 1 reports the top five European countries by installed hydropower capacity in 2018. It also shows the total generated HP and the difference between the maximum and minimum values of HP generation along the year [2].

Country	NST CAP (*) [MW]	ToT GEN [GW]	DIFF [MW]
Norway	28147	208570	29829
Spain	21125	153770	21945
France	19800	60538	11515
Sweden	17277	64036	13119
Italy	15559	44484	9494

Table 1: Top five countries by installed hydropower capacity (2018) (*) excluding pump-storage systems.

HP is either produced in run-of-river plants with low hydraulic heads and small reservoirs or from water stored in accumulation lakes with hydraulic heads up to several hundred meters, possibly with recirculation of water between lower and higher level reservoirs in so-called pump-storage systems. Among these existing technologies, the run-of-river based one is the most affected by meteorology and for this reason the most interesting to be studied. Typically, it generates electricity according to the water flow. This latter is defined by seasonal patterns of precipitations, evaporation, drainage, and other characteristics, which all depend on the geography and weather peculiarity of power plants locations. Figure 1 provides an overview

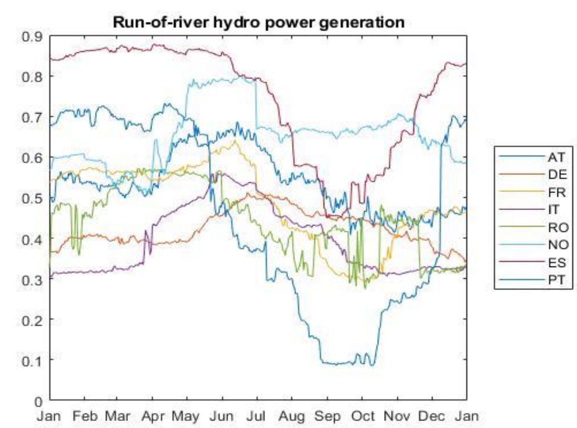

Fig 1: Estimated capacity factor of run-of-river hydro power generation over 2030.

on the variation of the run-of-river HP generation for some European countries obtained by considering climate forecasts over the year 2030. More details about climate data and the derivation of the HP prediction are provided in the next section. Although the seasonal patterns of wet and dry seasons are relatively predictable, they are not guaranteed and can change from one year to another. An assessment of climate change impacts on HP generation in different climate regions requires an in-depth analysis of individual case studies. Given the dominance of local conditions, generalizations are difficult, sometimes even for small regions. By what discussed so far it is clear that the definition of a common hydrological model for all European countries subject to different climate conditions is not an easy task. In this paper, we use Machine Learning (ML) techniques which have the advantage of catching specific trends and patterns in large volumes of data. The obtained models along with the forecast of climate data are then used for the prediction of the daily national HP generation in terms of capacity factor (i.e., fraction of produced power over the installed one) for all European countries. Although ML was already proposed in the literature for wind power and solar production and for the run-off forecast, as the best of our knowledge few attention has been dedicated to the long term HP impacted by long term climate forecast.

2. METHODOLOGY AND DATA COLLECTION

2.1 Methodology

ML has been gaining more and more importance in many areas of science, finance and industry. It is typically used to predict an outcome based on a set of features. Clearly, in the case of the present paper, the outcome is the HP generation and the features are the climate variables. The workflow of the ML procedure is given in Fig. 2. The procedure starts by training a so-called (supervised) learner with a set of data including the observed outcome and feature measurements. This leads to build a model, which enables predicting the unobserved outcome based on a different set of input features. A good learner is one that accurately predicts such an outcome. In order to select the ML technique that would provide the best prediction, we tested five well-established ML algorithms: Linear Regressor, Support Vector Machine, Boosted Ensemble of Trees, Random Forests (RF) and Artificial Neural Networks (ANN) [3]. The first four regression methods were implemented in the Statistics and Machine Learning Toolbox 11.4, while the ANN was in the Deep Learning Toolbox 12.0 in MATLAB® R2018b.

For the training and validation of ML models, observed climate and energy data are required. Meteorological data include the daily time series of precipitations and air temperature aggregated at NUTS 2 level. Historical climate data covering the period 1989 to 2018 are from Deutscher Wetterdienst [4].

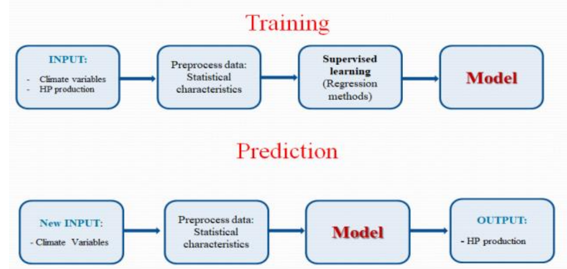

Fig 2: Machine Learning work flow

For the energy data, we considered values starting from 2010. Note that the lack of historical data of HP generation is a serious issue. Since January 2015, energy demand and generation data were collected at hourly time resolution for almost all countries in Europe and are available at the ENTSOE web server [2]. This dataset has been completed by data from the ECEM project [6].

In the validation phase, we compared the output model with observed data and we measured the performance of the five algorithms in terms of correlation coefficient, adjusted coefficient of determination, mean absolute and mean square percentage errors. This comparison indicated that the models based on Random Forests exhibit the best performance (e.g., correlation coefficient in the validation phase equal to 0.86 for France, 0.90 for Portugal and 0.95 for Spain). Hence, the results presented in this paper are obtained by using the RF algorithm.

2.2 *Future climate data*

The future projections are provided by [5]. These are generated by considering five combinations of global and regional climate models as listed in Table 2.

Notation	RCM	GCM
Mod1	KNMI-RACMO22E	ICHEC-EC-EARTH
Mod2	DMI-HIRHAM5	ICHEC-EC-EARTH
Mod3	IPSL-INERIS-WRF331F	IPSL-IPSL-CM5-MR
Mod4	MPI-CSC-REMO2009	MPI-M-MPI-ESM-LR
Mod5	SMHI-RCA4	ICHEC-EC-EARTH

Table 2: List of regional climate models (RCM) and global climate models (GCM).

Forecast of climate data are generated considering a Representative Concentration Pathways (RCP) set as both 4.5 and 8.5. These are scenarios including time series of emission and concentration of the full suite of greenhouse gases and aerosols and chemically active gases. The RCP4.5 is an intermediate stabilization pathway in which radiative forcing is stabilized at about

4.5 W/m^2, whereas for RCP8.5 the radiative forcing is assumed to reach values greater than 8.5 W/m^2 by 2100. Results presented in this paper refer only to RCP8.5. The projections cover the period from 2020 to 2060, and we are particularly focused on the target years 2030 and 2050. It is important to mention that climate projections are not an estimation of the year-to-year or season-to-season climate variables. Instead, they are estimations of the average conditions. Hence, for the prediction of HP generation over the years 2030 and 2050, for each climate model we generate time series of air temperature and precipitations as the average over 20 years centered in 2030 and 2050, respectively. Note also that for improving the prediction power of ML techniques, we selected climate times series based on the Europe map of Köppen climate classification shown in Fig. 3 [7]. For instance, this means that for the prediction of HP generation in Portugal, climate data of neighbor Spanish regions are used.

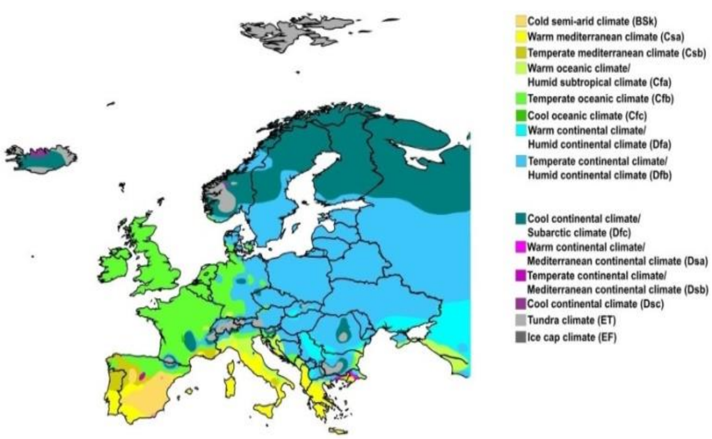

Fig 3: Europe map of Köppen climate classification.

3. RESULTS

In this section, we present the results obtained by the RF algorithm for the long term estimation of the HP capactity factor. Figure 4 shows the annual mean of the predicted capacity factor for the five different scenarios in Table 2. As expected, since we are looking at an average behavior, the results for all models are quite similar. The graphs show a predominance of Nord European countries, followed by the Iberian Peninsula, France, Italy and Nord East Europe. Figure 5 presents the anomalies of HP generation along the winter period (December-February) of 2050 with respect to 2000-2018. In general, the prediction is close to the historical mean value. These results can be explained by looking at the climate forecasts. For instances, for the winter period in France an increase of almost 1 °C and only 1 mm of precipitations is expected, instead in Portugal an increase of more than 2 mm of rains are predicted with only +0.5 °C in temperature. The highest anomalies are for Estonia and Ireland, followed by Portugal and Spain.

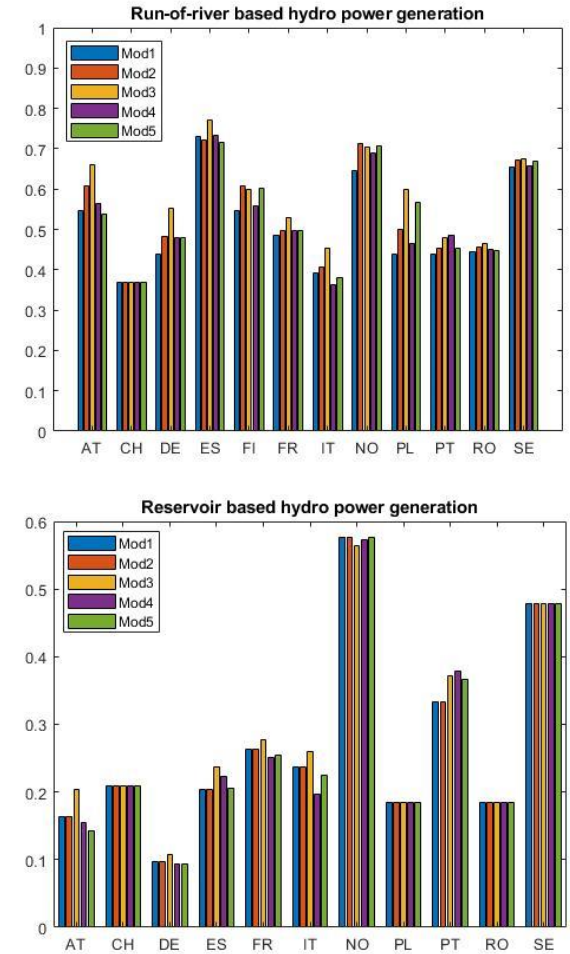

Fig. 4: Annual mean of HP generation obtained by considering the five climate models over the year 2050.

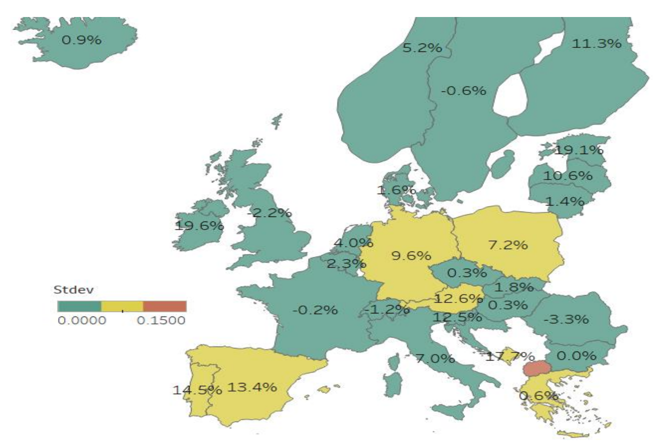

Fig 5: Anomalies in the run-of-river HP generation for the year 2050 (winter period **DJF)**.

Yet there are strong limitations of using only these average behaviors for future power generation assessment in Europe. In fact, to give a coherent picture of the future variability in HP generation in each country we need to consider the calendar variability of capacity factors, the variability induced by the different future climate models, and the variability associated to the sliding window of 20 years around each target year. As an example, we show the variability of the capacity factor along 20 years centered in 2050 in Portugal and France in Fig.s 6 and 7. From the perspective of the interconned European power system, Portugal and France are two archetypes of a peninsula and a highly interconnected systems.

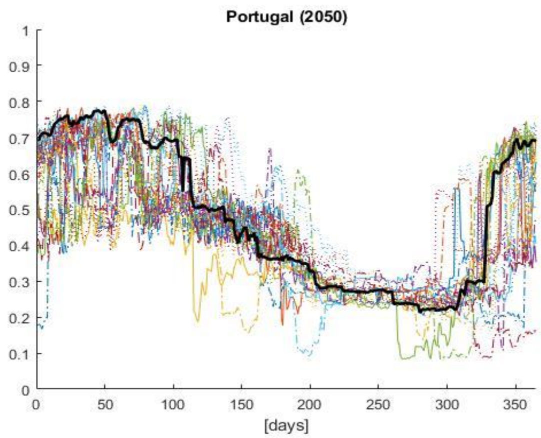

Fig 6: Variability of capacity factor over 20 years around 2050 for Portugal by using climate model Mod3.

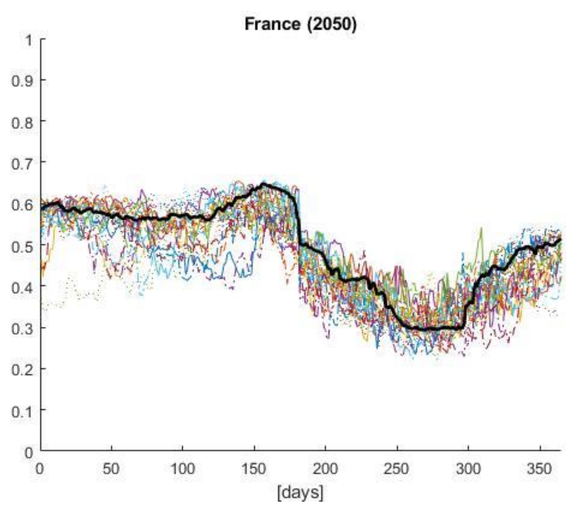

Fig 7: Variability of capacity factor over 20 years around 2050 for France by using climate model Mod2.

Estimated 2050 capacity factors for HP generation in Portugal vary more strongly. This is in line with a more complex Köppen climate classification. During the winter period the values are within the interval 0.4-0.79, with one critical year where the capacity factor is 0.19 in January. The lowest value is achieved during one the 20 summer periods (August) when the capacity factor is about 0.07. The more uniform Köppen map for France justifies the smaller variability of the capacity factor in this country.

4. CONCLUSIONS

Europe is expected to strongly expand its wind and solar power capacity by 2050 to meet its climate goals. In an interconnected system, balancing these highly intermittent sources by hydro power will also involve a European wide evaluation of the variability of HP generation for future climatic conditions. The methodological framework described in this paper offers the possibility of addressing this issue. The two main ingredients are: the formalization of an accurate ML model and the long term climate forecasts. Their combination provides an overview of the long term variability of capacity factors at country scale for Europe.

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