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Seasonal climate forecasts for medium-term electricity demand forecasting

Matteo De Felice [a,*], Andrea Alessandri [a,b], Franco Catalano [a]

[a] Casaccia R.C., ENEA Energy and Environment Modelling Technical Unit, Rome, Italy
[b] International Pacific Research Center, University of Hawaii at Manoa, Honolulu, HI, USA

HIGHLIGHTS

- During the ten years, seasonal climate forecasts have improved their skill.
- We analyzed the link between summer average temperature and demand over Italy.
- Both deterministic and probabilistic forecasting approaches are here considered.
- Climate forecasts show a significant skill in predicting the demand in many regions.

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ABSTRACT

Air temperature is an effective predictor for electricity demand, especially during hot periods where the need of electric air conditioning can be high. This paper presents for the first time an assessment of the use of seasonal climate forecasts of temperature for medium-term electricity demand prediction. The retrospective seasonal climate forecasts provided by ECWMF (European Centre for Medium-Range Weather Forecasts) are used to forecast the June–July Italian electricity demand for the period 1990–2007.

We find a relationship between summer (June–July) average temperature patterns over Europe and Italian electricity demand using both a linear and non-linear regression approach. With the aim to evaluate the potential usefulness of the information contained into the climate ensemble forecast, the analysis is extended considering a probabilistic approach.

Results show that, especially in the Center-South of Italy, seasonal forecasts of temperature issued in May lead to a significant correlation coefficient of electricity demand greater than 0.6 for the summer period. The average correlation obtained from seasonal forecasts is 0.53 for the temperature predicted in May and 0.19 for the predictions issued in April for the linear model, while the non-linear approach leads to the coefficients of 0.62 and 0.36 respectively. For the probabilistic approach, seasonal forecasts exhibit a positive and significant skill-score in predicting the demand above/below the upper/lower tercile in many regions.

This work is a significant progress in understanding the relationship between temperature and electricity demand. It is shown that much of the predictable electricity demand anomaly over Italy is connected with so-called heat-waves (i.e. long lasting positive temperature anomalies) over Europe.

1. Introduction

The main goal of this work is to investigate the use of seasonal climate forecasts for electricity demand over Italy, focusing on the summer period between 1990 and 2007. During the last decade, climate forecasts have significantly improved their skill on seasonal time-scales (from one month to six months) [27,5,22,4] but their application to decision-making processes are still rare on scientific literature. Considering also the challenges raised by the recent FP7 European Projects on Climate Services (CLIMRUN [1], SPECS [3], EUPORIAS [2]), this paper provides an initial assessment of the use of seasonal climate predictions for power systems management with the focus on electricity demand (load) forecast at lead times of one and two months.

* Corresponding author.
E-mail addresses: matteo.defelice@enea.it (M. De Felice), andrea.alessandri@enea.it (A. Alessandri), franco.catalano@enea.it (F. Catalano).

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Given the necessity of ensuring the balance between electricity production and demand, an accurate estimation of future weather state could improve the efficiency and reliability of energy management at local and national scales. In fact, weather is a crucial element both for the generation and demand of electricity [25,16] The relationship between temperature and demand is well-known and it has been already investigated in many works focused on Europe. Valor et al. [28] and Pardo et al. [24] first recognized the strong coupling between electricity demand and temperature. Furthermore Bessec and Fouquau [9], analysing 15 European countries over twenty years, put the emphasis on the increasing sensitivity of electricity demand with respect to temperature during the recent years. On Italy, load forecasting has been analyzed by Bianco et al. [10] and De Felice et al. [17] at short time scales. However, the predictability of the medium-term load and the usefulness of seasonal climate forecasts at this time-scale need to be understood.

This paper focuses on Italian demand during summer. Due to the high temperatures that can be reached in many Italian regions, power grid can experience high demand peaks especially considering the increasing use of air conditioning, which have drastically increased the sensitivity of demand with respect to temperature in the last decade (an analysis of this phenomenon can be found in De Felice et al. [17]).

The effectiveness of seasonal climate forecasts for electricity demand forecasting is here analyzed both considering deterministic and probabilistic approaches. Probabilistic predictions allow for the reliable forecasting of future dichotomous events [19]. This information can be of particular value in situations where probabilities of different outcomes are needed in advance to make an optimal decision. To this end, instead of evaluating the difference of the ensemble mean from the target demand (deterministic approach), we evaluate the probability from the ensemble forecast in predicting a demand above/below normal (defined as the upper/lower tercile of the observed demand distribution).

After the description of the applied method in Section 2 we introduce and analyze the weather and climate data used in this paper in Sections 3.1 and 3.2 respectively. Section 4 provides a description of the probabilistic measures used in the rest of the paper. Then the results for the deterministic and probabilistic approaches are described respectively in Sections 5.1 and 5.2. All the results are discussed in Section 6 where we also provide an in-depth analysis on the relationship between heat-waves and electricity demand in Section 6.1. Finally, conclusions of this paper are reported in Section 6.2 outlining the future steps of this research.

2. Method

All the results shown in this paper have been obtained considering two regression approaches: a linear regression model and a Support Vector Machine, a well-established non-linear method.

2.1. Linear regression

Our linear approach has been inspired by Navarra and Tribbia [23] and it is based on the assumption of linearity between two fields, here denoted respectively with $\mathbf{Z}$ and $\mathbf{S}$.

Considering the equation $\mathbf{Z} = \mathbf{AS}$ we compute $\mathbf{A}$ matrix solving the least squares minimization problem:

$$\mathbf{A} = \mathbf{ZS}'(\mathbf{SS}')^{-1} \tag{1}$$

Finally we obtain the forced by field as:

$$\mathbf{Z}_{\mathbf{forced}} = \mathbf{AS} \tag{2}$$

It is worth noting that the residual $\mathbf{Z}_{\mathbf{free}} = \mathbf{Z}_{\mathbf{forced}} - \mathbf{AS}$ represents the variability of $\mathbf{Z}$ not connected with the variability of $\mathbf{S}$.

To reduce significantly the dimension of both data matrices, we applied Principal Component Analysis (PCA) using coefficients instead of original data, retaining the 99% of the total variance. Thus projecting $\mathbf{Z}$ and $\mathbf{S}$ into the principal component space we obtain respectively $\widetilde{\mathbf{Z}}$ and $\widetilde{\mathbf{S}}$, both with the selected modes as columns.

Using the PCA approach, Eq. (1) becomes:

$$\mathbf{A} = \widetilde{\mathbf{Z}}\widetilde{\mathbf{S}}'(\widetilde{\mathbf{S}}\widetilde{\mathbf{S}}')^{-1} \tag{3}$$

As suggested in Cherchi et al. [12] we can remove the least significant parts of $\mathbf{A}$ matrix (see Eqs. (1) and (3)) using a significance test. Here we put to zero all the coefficients of $\mathbf{A}$ that do not fit the confidence intervals of a 10% Student t-test for the correlation between $\mathbf{Z}$ and $\mathbf{S}$.

2.2. Support Vector Machine (SVM)

SVMs were developed by Cortes and Vapnik [13,29] for binary classification and then extended to regression problems (Support Vector Regression). The idea behind support vector-based methods is to use a non-linear mapping Φ to project the data into a higher dimensional space where solving the classification/regression task is easier than in the original space.

Following an approach similar to the linear method, we can think the SVM as a non-linear function $f(\cdot)$:

$$\mathbf{Z}_{\mathbf{forced}} = f(\mathbf{S}) \tag{4}$$

In our case, we used a Support Vector Regression method called ϵ-SVR [15], which tries to find a function $f(x) = \langle w, \Phi(x)\rangle + b$ that has at most ϵ deviation from the target values. A ϵ-SVR model has three parameters: the regularization parameter C, the ϵ value, and the width of the radial kernel γ.

The selection of the SVR model parameters has been carried out applying a grid search among 54 combinations of $C \in [10^{-1}, 10^{1}], \epsilon \in [10^{-2}, 1])$ and $\gamma \in [2^{-10}, 2^{2}]$. The parameters used through our work are the following: $C = 10, \epsilon = 10^{-2}, \gamma = 2^{-10}$.

As we did for the linear model, we use the PCA technique to reduce the dimensionality of $\mathbf{S}$ and $\mathbf{Z}$ spaces, considering pattern coefficients instead of the original data fields.

3. Data

3.1. Climate data

A seasonal climate forecast provides information about future climate conditions with a lead-time of one to six months. In this work, we use retrospective forecasts produced by the ECMWF[1] System 4 forecast system. This prediction system has been adopted as operational system since November 2011 [22]. For a detailed analysis of the seasonal prediction skills of System 4 forecasting system we refer to the works by Kim et al. [20] and Doblas-Reyes et al. [14].

Forecasts are issued monthly, here we consider two different starting months: April and May. For each starting month we used the predicted values of temperature fields for June and July, i.e. respectively with two and one month of lead time.

A way to deal with the complexity and uncertainties of the climate system is to use an ensemble of predictions, i.e. having at each starting date a set of forecasts each with slightly different initial conditions. System 4 has 51 ensemble members for the starting date in May 1st and 15 for April 1st. Fig. 1 shows an example of an

[1] ECMWF www.ecmwf.int. is an intergovernmental organisation which provides operational forecasts and super-computing facility for scientific research