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Complex Dynamics of Photovoltaic Outputs

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Abstract—We analyze a dataset of photovoltaic outputs measured at 61 points within Japan. First, we apply the method of Non-Negative Matrix Factorization, and obtain a sparse non-negative decomposition of the dataset. Second, we examine interactions among components of the decomposition. We find that photovoltaic outputs represent complex interactions of the atmosphere.

1. Introduction

We must introduce more photovoltaic outputs worldwide because we need to reduce CO_2 emission and circumvent oil depletion. However, if we try to introduce more photovoltaic outputs to power grid systems, the systems may become unstable because photovoltaic outputs fluctuate due to the weather conditions. To overcome the natural fluctuations of photovoltaic outputs, we should understand the dynamics of the weather generating the photovoltaic outputs more deeply.

To achieve this goal, here we analyze a time series of photovoltaic outputs to reveal their complex dynamics. Important characteristics related to photovoltaic outputs are one-day-periodicity, one-year-periodicity, and non-negativity. While the periodicities are often taken into account, non-negativity has been ignored when we analyzed the time series data. However, because the non-negativity is an essential property of photovoltaic outputs, we use Non-Negative Matrix Factorization [1] to decompose the photovoltaic outputs. Then, we evaluate interactions among components of the decomposition by a method of Ref. [2], which uses recurrence plots [3, 4] and delay coordinates for forced systems [5]. Furthermore, we verify the obtained interactions with the extension [6] of Judd and Mees method [7].

We will find complex interdependences among the components of photovoltaic outputs.

2. Dataset

The dataset we use was a time series of photovoltaic outputs measured at 61 points in the central part of Japan. The observation period is between November 2010 and April 2012. Although the original dataset has a value every 10 seconds for each point, we take the average over 1 hour and analyze the averaged time series.

3. Methods

3.1. Non-Negative Matrix Factorization

Non-Negative Matrix Factorization [1] (NNMF) approximates a matrix A by the multiplication WH of two matrices W and H so that each element of the two matrices W and H is non-negative. By NNMF, we can obtain a sparse expression because the number of rows in W and the number of columns in H are small.

Because the results of NNMF depend on the initialization, we run NNMF 100 times for each number of rows in W by changing the initial conditions.

The number of rows in W and the number of columns in H are decided so that the Akaike Information Criterion [8, 9] becomes the smallest.

We apply NNMF to the dataset of photovoltaic outputs, where each row corresponds to one of measured points and each column corresponds to an hour on the time axis.

3.2. Estimating directional couplings

Then, H can be regarded as a time series whose rows correspond to characteristic columns of W. Therefore, we estimate directional couplings among these characteristic columns. We use the method in Ref. [2]. The method of Ref. [2] tests whether two time series are related or not. If two components are related, then we test whether there are directional couplings between them or not. If two components are related and both directional couplings are denied, then only a possibility is that there exists a common hidden element driving two components. To deny the directional couplings, we use recurrence plots [3, 4] and delay coordinates for forced systems [5]. If x drives y, there are significant thresholds for recurrence plots such that the recurrence plot of x obtained using delay coordinates can cover the recurrence plot of y obtained using delay coordinates. We use its contra-position: If there are no significant thresholds such that the recurrence plot of x can cover the recurrence plot of y, then x does not drive y. By the contra-position, we can deny the directional coupling from x to y.

In addition, we use the method of Ref. [6], which is the extension of Judd and Mees [7], to validate the directional couplings obtained by the method of Ref. [2]. Namely, we check whether the directional couplings obtained by the method of Ref. [2] actually contribute to improving the prediction for each component or not.

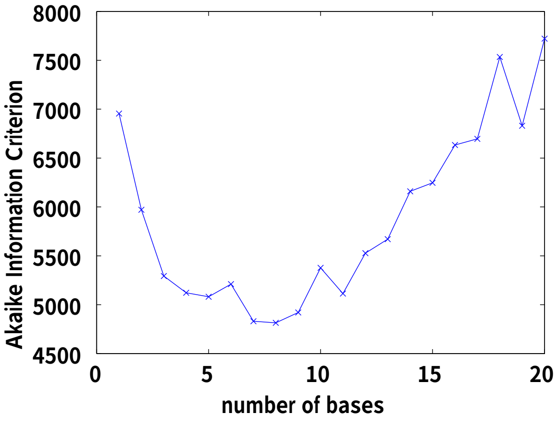

Figure 1: The number of rows in W vs the Akaike Information Criterion. We choose 8 as the optimal number of rows in W because the number minimizes the Akaike Information Criterion.

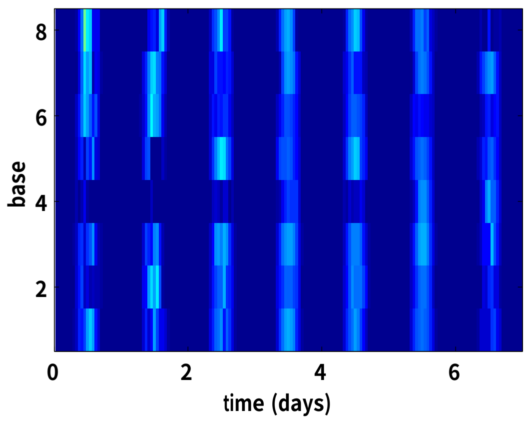

Figure 3: Temporal changes of H.

4. Results

We first minimize the Akaike Information Criterion to obtain the optimal number 8 of rows in W (Fig. 1). Then, we interpolate each column vector of W by using the longitude and the latitude of each measured point. Then, each column vector tends to have a local peak spatially (Fig. 2). This tendency means that each column vector can be regarded as a local irradiation condition centered at the peak.

The matrix H can be regarded as a time series of characteristic columns in W, part of which is shown in Fig. 3. It seems that each row of H changes according to the weather conditions. In addition, it is not clear how these rows interact with each other.

To resolve the interactions, we use the methods of Refs. [2] and [6], simultaneously. The obtained directional network is shown in Fig. 4. The network implies that the bases 1, 2, and 3, which have their peaks close to the center of the analyzed region, tend to depend on the bases of the surrounding area.

5. Discussion

The results shown in Fig. 4 mean that the weather conditions, and thus photovoltaic outputs, have complex dynamics, which cannot be separated into pieces easily. Bases 4-8 were not explicitly driven by the other bases possibly because the peaks of these bases were located at the edges of the considered region. Therefore, if we extend the region to a wider area, these bases will be also in a well connected network that cannot be separated easily.

6. Conclusions

We have investigated the underlying dynamics behind the photovoltaic outputs. After decomposing the photovoltaic outputs into non-negative components, and inferring directional couplings, we found that there are complex interdependences among local photovoltaic conditions which cannot be separated into pieces easily. We will try to predict photovoltaic outputs by using this obtained knowledge well.

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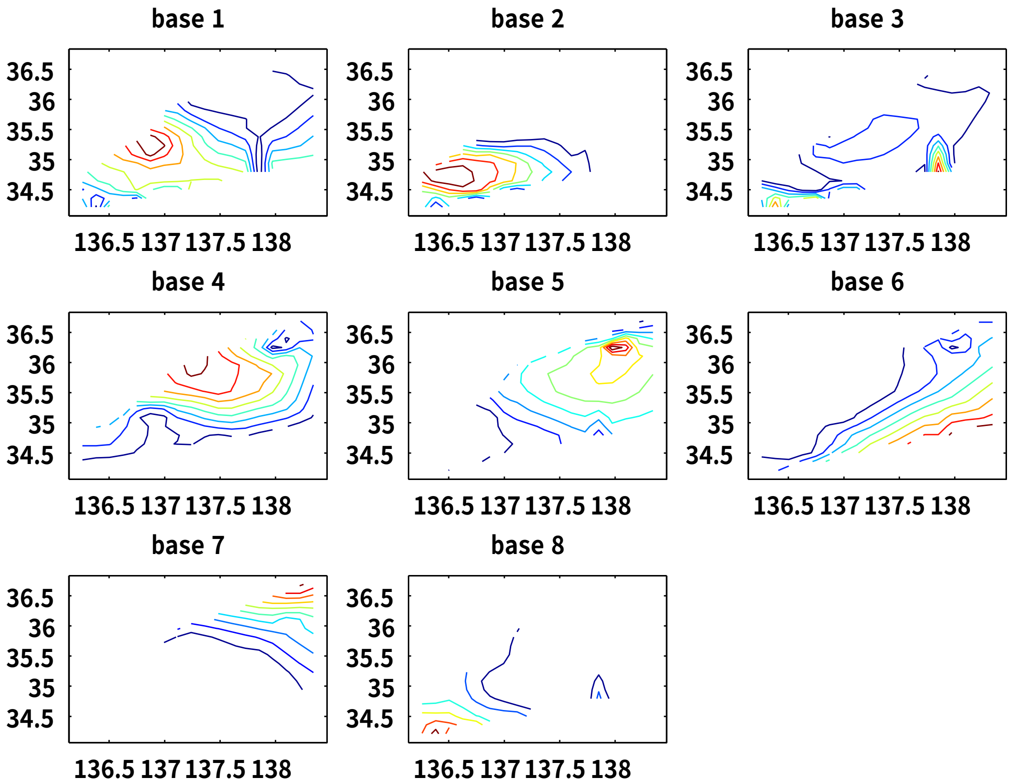

Figure 2: The column vectors of W represented by an interpolating function spatially. Each panel represents each column vector, which we call a base.

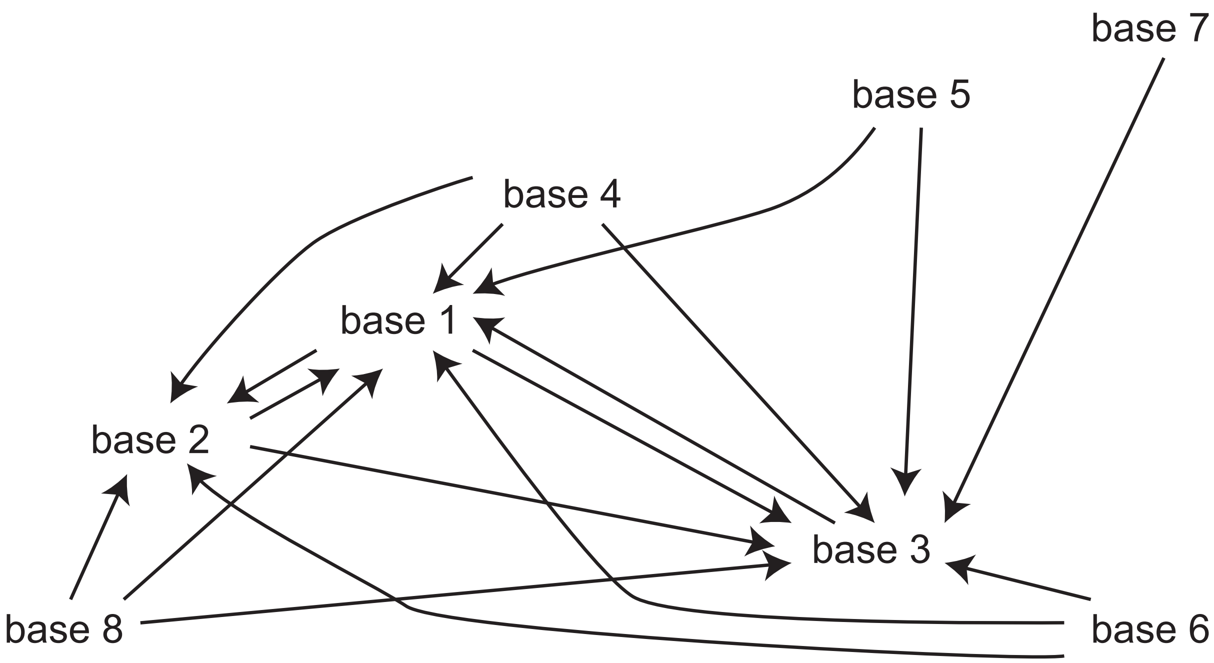

Figure 4: Directional couplings among bases of photovoltaic outputs. The position of each base is located according to the longitude and the latitude of the peak of each base shown in Fig. 2. Each arrow means that there is a directional coupling from one base to the other.

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