

# Chapter 2

## Time Series Prediction of Renewable Energy: What We Can and What We Should Do Next

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**Abstract** We summarize our recent developments of time series prediction for renewable energy. Given the past parts of high-dimensional time series for renewable energy outputs, we can predict their multistep future in real time with confidence intervals. We also proposed a way to evaluate the closeness in the high-dimensional space for improving the prediction, and an index showing when the prediction is more likely to fail. In addition, it is straightforward to apply the proposed framework to predict the electricity demands. Therefore, we can generate information necessary to consider efficient unit commitments for a case where more renewable energy resources are installed.

**Keywords** Online multistep prediction · High-dimensional time series · Confidence intervals · Prediction credibility · Renewable energy · Electricity demands

### 2.1 Introduction

Because we need to reduce CO<sub>2</sub> mission to mitigate the impacts of the climate change, we need to introduce more renewable energy. However, because renewable energy outputs fluctuate due to the changes of weather conditions, we should predict the temporal changes of renewable energy outputs and demands, and prepare backup plants such as thermal power plants and hydroelectricity power plants so that the supplies of electricity match its demands.

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When we predict renewable energy outputs and electricity demands, our prediction should be done in real time, provide estimates for multiple steps ahead simultaneously, and show uncertainties representing how reliable these predictions are. We have been developing methods of time series prediction that meet these requirements [1–4]. Because we only use the past observations of interested quantities that should be forecasted, we can provide the predictions of renewable energy outputs and electricity demands simultaneously by the method described in [1–4] when we have their past time series data.

In this chapter, we first summarize our recent developments of such time series prediction methods. Then, in Sect. 2.3, we show some examples of time series prediction for electricity demands. In Sect. 2.4, we discuss necessary techniques for controlling and/or scheduling power plants, and conclude this chapter.

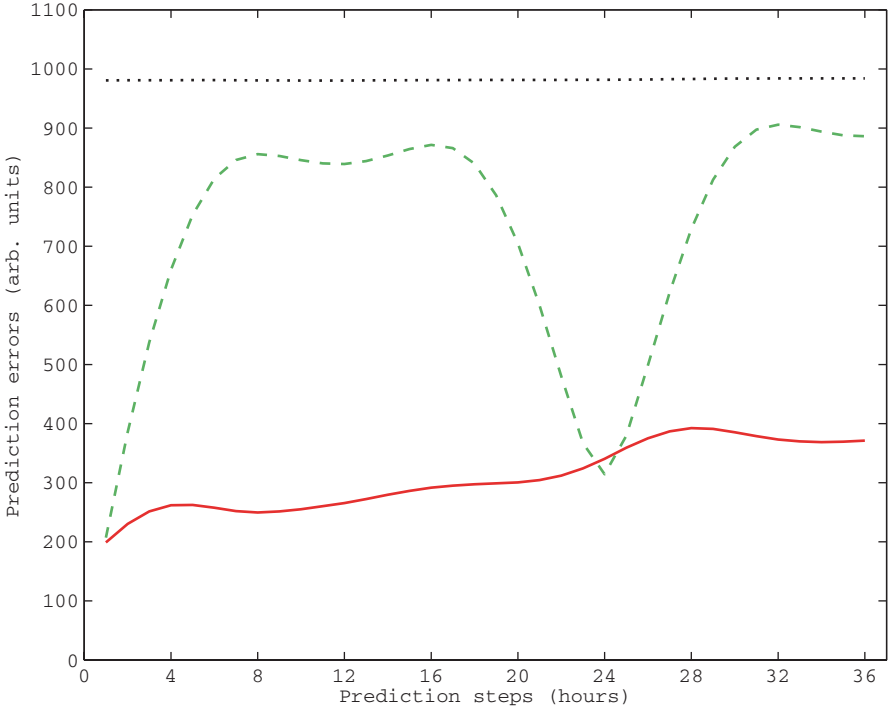
## 2.2 Online Time Series Prediction

We discuss the method we recently proposed [1–4] for predicting renewable energy resources, which is based on the method of Kwasniok and Smith [5]. Suppose that we constructed a database of past temporal changes of renewable energy outputs. Then, at each time, the method requires us to conduct two steps: In the first step, we find close matches to the current state within the database, and follow the time evolution of these close matches to obtain confidence intervals for the future values of multisteps ahead. In the second step, we observe the next value and update the database so that we can keep the size of the database but possibly reduce the prediction errors. In Ref. [1], we proposed the basic framework for online multistep prediction. In Ref. [2], we obtained confidence intervals. In Ref. [3], we extended the method to multivariate data in such a way that the prediction errors become smaller by evaluating the  $p$ -norm between two states where  $p < 1$  [6] than by using the normal Euclidean distance for evaluating the closeness between these two states. In Ref. [4], we introduced an index for evaluating when the proposed method is more likely to fail by evaluating the metric of the current state to the neighboring states in the database. This new index is information that is complementary to maximal local Lyapunov exponents [7, 8], which evaluate how fast the prediction errors grow as the prediction step becomes longer.

Therefore, we can evaluate, using the methods described in Ref. [1–4], what predicted values are, how large the prediction errors will be, and how faithful the prediction is.

## 2.3 Example for Predicting Electricity Demands

To demonstrate the framework of our recent developments, we apply the time series prediction discussed above to the prediction of electricity demands. The dataset was downloaded from the homepage of the Tokyo Electric Power Company



**Fig. 2.1** Prediction errors for the mean for the proposed method (*red solid line*), the persistence prediction (*green dashed line*), and the mean prediction (*black dotted line*)

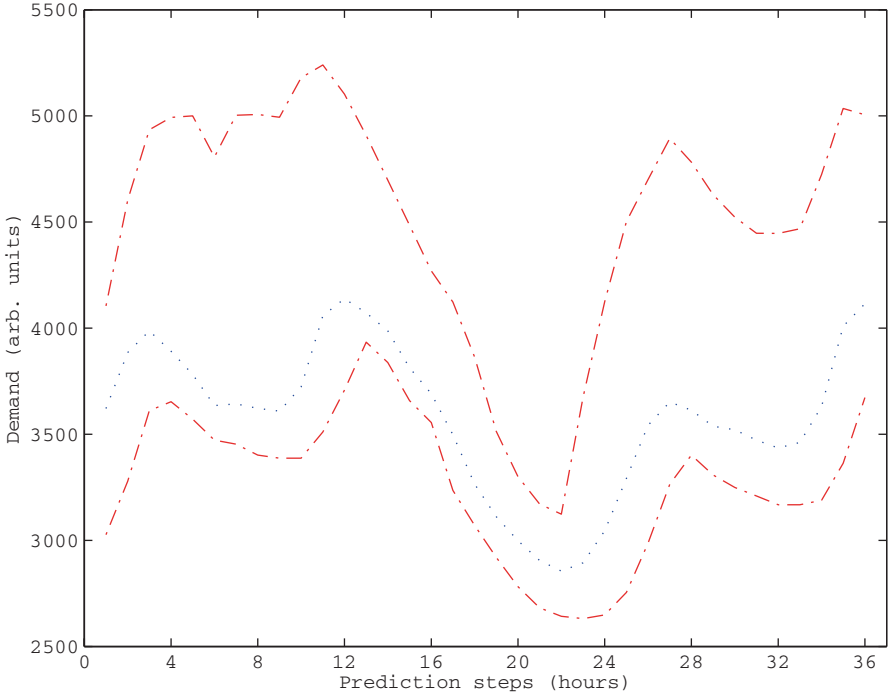
(<http://www.tepco.co.jp/en/forecast/html/download-e.html>). The dataset was hourly measurements between 1 January 2010 and 28 February 2011 (because the Tohoku-Oki earthquake of 11 March 2011 caused big changes in the electricity consumptions, we used the part of the dataset before the earthquake occurred).

The prediction errors are shown in Fig. 2.1. The mean for the proposed method enjoyed its advantage when the prediction step is less than 24 h compared with the persistence prediction, within which we let the current value for the prediction of  $q$  hours ahead.

We show in Fig. 2.2 an example of our prediction. Because this is the period in winter, there seemed to exist two peaks in the electricity demand within a day: morning and evening.

In Fig. 2.3, we compared the case where the metric to the datasets in the database was shorter than its median with the case where the metric was larger than its median. We clearly saw that 96% confidence intervals had a higher confidence level when the metric was short, while the difference was statistically significant for only a limited number of prediction steps, especially those between 2 and 6 h when we evaluated the difference using the chi-square test.

Summing up, the above prediction for the electricity demands presented similar to the prediction for solar irradiation discussed in [3, 4].

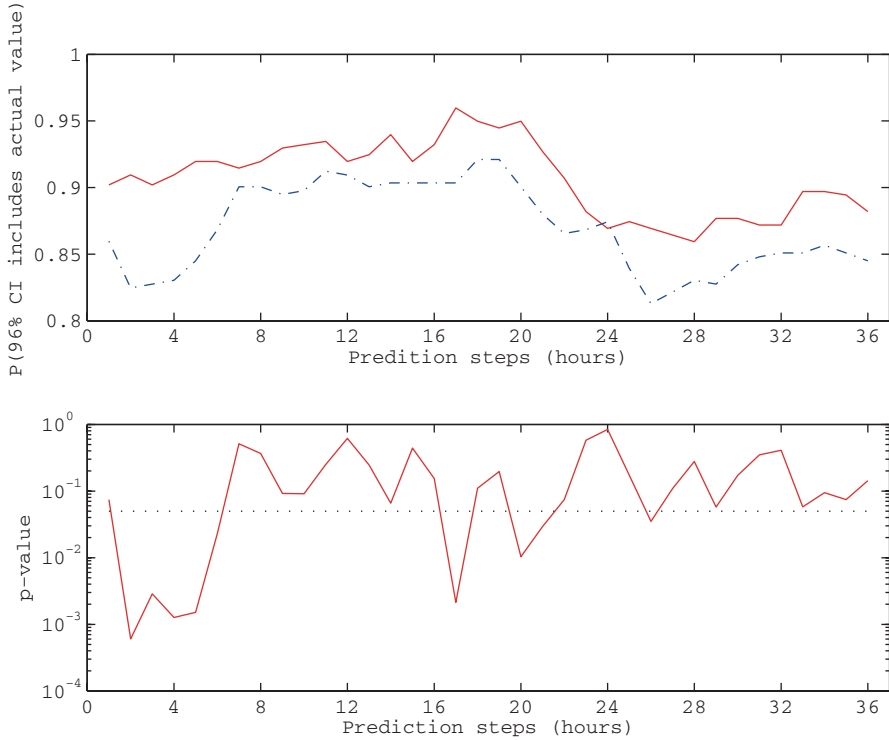


**Fig. 2.2** Example of prediction for the electricity demands. The *red dot-dashed lines* show 96% confidence intervals of prediction. The *black dotted line* shows the actual value

## 2.4 Discussion

We described our recent developments for predicting time series. The method for the time series prediction can run online, span multiple steps ahead, and produce confidence intervals. In addition, we also proposed to use the  $p$ -norm with  $p < 1$  for evaluating the closeness in the high-dimensional space, which improves the accuracy of the prediction. Moreover, we derived an index for showing when the prediction is more likely to fail. Because the developed method uses the deterministic property for the underlying dynamics, we can apply the same method to predict the electricity demands. Thus, we now potentially have sufficient information to solve the problem of unit commitments, by which we can make power grid systems with much renewable energy sources more reliable. Therefore, we should try to optimize unit commitments robustly so that we can ensure the efficiency and the flexibility of our plan of starting and/or stopping backup power plants to meet supplies and demands of electricity.

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**Fig. 2.3** Credibility of predicted confidence intervals. The *top* panel shows the probability that the actual values are contained within 96% confidence intervals given a prediction step. The *red line* shows the probability that the metric was small, and the *blue dash-dotted line* shows the probability that the metric was large. The *bottom* shows the *p*-values for the difference between the cases where the metrics were small and large, respectively

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