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Very short-term maximum Lyapunov exponent forecasting tool for distributed photovoltaic output

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HIGHLIGHTS

- The chaotic characteristic of photovoltaic (PV) output from a microgrid is verified.
- A Maximum Lyapunov Exponent method for PV forecasting is proposed.
- The feature of the method is nonlinear, very short-term and lower-experimental-cost.
- The method is validated for minute-ahead PV output forecasting.
- The performance is validated using a demonstration PV system in southeastern China.

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ABSTRACT

Photovoltaic (PV) power generation varies randomly and intermittently with respect to the weather. For a microgrid with PV sources, this fluctuation not only affects the necessary configuration of the energy-storage capacity chosen in microgrid planning and design but also influences the microgrid operation. Consequently, accurately forecasting the PV output is crucial. For the operation of a PV-dominated microgrid, a new method for very short-term (VST) forecasting based on the maximum Lyapunov exponent (MLE) is proposed. First, historical power-generation data are divided into three weather conditions: sunny, cloudy, and rainy days. Then, a PV output series for the different weather conditions is constructed, and the chaotic characteristic is verified by reconstructing an attractor graph and calculating the MLE. Finally, using the MLE method, the PV generation under different historical weather conditions is forecasted. The raw output time series are measured data from a demonstration system installed on the rooftop of Building 6 at Hangzhou Dianzi University, China. The forecasting accuracy is evaluated using several statistical metrics and compared with that of forecasts obtained via the widely used auto-regression approach. Comparing the forecasts indicates that the MLE-based method is statistically but not universally more accurate for VST forecasting.

0. Introduction

Renewable energy resources should replace traditional power generation because of their desirable characteristics of sustainability and low pollution. Considering this criterion, photovoltaic (PV) electricity generation is an excellent renewable energy source, but its output varies significantly depending on the weather, especially in cloudy climates such as that of southeastern China. PV power is both uncertain and random. On one hand, the connection of large-scale PV systems to the utility grid might affect the safety and reliability, raising the barrier to its large-scale utilization. On the other hand, if demand is served locally by PV within a microgrid, even at low solar penetration (i.e., the solar generation percentage in total power generation for a district), stability problems can arise for microgrid operation; e.g., it might be difficult to maintain the voltage and frequency in an islanded PV-dominated inertia-less microgrid. Using battery banks large enough to smooth inevitable demand–supply imbalances is the usual strategy, but it significantly increases the capital costs and can lead to pollution from battery disposal. All of these effects have economic implications for future microgrid viability. Accurate forecasting of the PV power can provide important input to microgrid power dispatching and operation by facilitating adjustments to the operational plan in time to optimize the performance and minimize the cost [1,2]. In addition to the benefit to the operation of utility grids and microgrids, solar forecasting has been proven to be helpful in other fields, such as marine power supply systems [3]. Because the randomness and variability of the PV output

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Nomenclature

m	embedding dimension
d	correlation dimension
τ	delay time
$\{x_t\}$	time-series data set
n	length of time series
$\{X_s\}$	phase point set in reconstructed phase space
N	number of phase points in reconstructed phase space
X_{s_0}	initial phase point
$X_{s'0}$	adjacent phase point
L_0, L_1	Euclidian distance
ε	predetermined threshold
L'_0	Euclidian distance exceeding ε
Δs	time step
M	total steps for calculating $\lambda_{\max}$
$\lambda_{\max}$	maximum Lyapunov exponent
P	average period
T	forecast horizon
$F(k)$	kth frequency component in FFT
$FFT(\cdot)$	fast Fourier transform
$MAX(\cdot)$	maximum value
$Round(\cdot)$	rounded value
K	frequency of maximum frequency components
E_{MAPE}	mean absolute percentage error
E_{rRMSE}	relative root-mean-square error
E_{MBE}	mean bias error
W	forecasted PV power generation
$\widetilde{W}$	measured PV power generation

can be mitigated by accurate forecasting and its full use is encouraged by policy, solar forecasting has received considerable attention in the literature.

The long history of research on forecasting PV generation has been fruitful. Fundamentally, the technology can be divided into two categories: physical modeling and data-driven methods. The physical-modeling approach focuses on studying equivalent circuits of PV cells to forecast the power output based on predicted weather input parameters, such as irradiation and temperature [4]. These models can require many circuit parameters, such as series resistance, shunt resistance, diode reverse saturation current, photocurrent, diode impact factor, and various temperature coefficients. Acquiring some of these data sets requires complex calculations, while others can be provided by manufacturers. For example, [5] used a physical model requiring a large amount of raw sampled data to estimate the PV system parameters used in a simulation. Consequently, physical modeling has limited real-world application, and data-driven methods are used more often in practice. Further, rapid progress in data processing, artificial intelligence, and machine learning are giving data-driven methods a stronger advantage, and they are now widely used in various forecasting applications [6].

Data-driven methods can be subdivided into linear and nonlinear models, from a mathematical viewpoint. The popular linear models applied in PV forecasting are auto-regression (AR), auto-regressive extrapolation [7], and auto-regressive moving-average extrapolation (ARMAX) [8]. These models are simple in structure but inflexible [9], and the actual PV output is absolutely nonlinear; thus, many researchers focus on studying nonlinear forecasting. Among the nonlinear models, the artificial neural network [10], the support vector machine [11], and their enhanced counterparts combined with other composite methods are widely used [12,13]. In a previous study [14], eleven prediction models were compared, including linear methods, nonlinear methods, and ensemble algorithms. Compared with the linear methods, the nonlinear and ensemble approaches significantly improved the precision.

Data-driven forecasting methods can also be subdivided into three models according to the raw data used: time series [15], numerical weather prediction (NWP) [16], and sky imaging [17]. Time-series models are based only on historical PV generation data. No other input data are necessary; thus, there are no experimental requirements. Linear models such as AR and auto-regressive moving-average (ARMA) and their extended versions are typically used for time series, while nonlinear time-series models are not common. NWP is commonly used with control inputs [7]. With the progress of image processing, predicting the PV output via sky imaging is attracting attention from researchers. This method takes ground-based or satellite cloud images and forecasts their movement and shading, thereby predicting surface insolation [18,19]. Which model should be used depends heavily on the experimental conditions and available information. For example, NWP methods need considerable weather data,

while sky imaging requires satellite cloud pictures or all-sky imaging equipment, both of which are expensive.

With regard to the time horizon, PV forecasts can be categorized as long-term, short-term, or very short-term (VST), but researchers have very different ideas about the time cutoffs. For example, in [20] and [21], the VST horizon was defined as several minutes to several hours, the short-term horizon ranged from a few hours to 3 d, and the long-term horizon ranged from a week to a year. In [22], short-term was defined as 5–8 min. Regardless of how the forecast periods are defined, their roles are similar. The VST forecast aims at intra-day real-time control and power-market participation; the short-term forecast is used for day-ahead economic dispatch; and the long-term forecast focuses on equipment maintenance scheduling, market participation, etc. [23]. For these three time domains, researchers have addressed current problems in short-term forecasting [24,25]. For example, in [26], a model-based predictive control approach was applied with short-term direct normal irradiance forecasting for optimal scheduling in concentrating solar power plants.

A shorter horizon means that the forecast is more conducive to an emergency response, making VST PV forecasting particularly crucial. VST PV behavior is mainly affected by cloud movement; thus, this forecast mainly uses the aforementioned NWP, sky images, sensor arrays plus random-sequence, time series, etc. [27]. These methods make it possible to achieve a precise forecast, but they are limited by the measurement equipment available. For example, cloud imaging of the entire sky requires a fish-eye lens mounted on a whole-sky camera with an unrestricted panoramic view of 180° in every direction. These devices are not only expensive but also limited in space–time resolution, and there are shortcomings in the PV forecast.

Although there are many methods for forecasting, it is difficult to say which one is better, given different time scales, geographies, PV capacities, and experimental conditions [28,29]. This paper summarizes the advantages and disadvantages of the aforementioned AR forecast methods compared with a proposed VST forecast method based on the maximum Lyapunov exponent (MLE) approach, which analyzes the chaotic characteristic of an actual evolving PV generation time series.

While the traditional AR method has good linear forecast performance, MLE—being a nonlinear time series analysis method—provides greater accuracy. Given the sensitivity of chaotic systems, MLE does not directly construct a mathematical model linking the output to its influencing factors; instead, it describes the evolution of the dynamic system according to the exponential separation characteristic of the actual chaotic data, yielding a nonlinear time series VST forecast. The approach does not require complex experiment or expensive equipment, and no procedures are needed to estimate parameters for initial