Chaos Model for Photovoltaic Power Prediction based on Laguerre Polynomials and Information Entropy

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***Abstract*—Improvement of the performance, stability and security of power systems is of great significance. In this paper, the mechanisms of chaotic behavior and photovoltaic power predictions are discussed on the basis of phase space reconstruction of chaotic dynamic systems. The analysis shows that photovoltaic power has both chaotic and random components, which is in accordance with the experimental data. By combining the advantages of the orthogonality of Laguerre polynomials and the approximation effect of a local chaos prediction model, a chaos model for photovoltaic power prediction is presented based on information entropy and is applied to replace the Euclidean distance in choosing the weight of the fitting phase points in the reconstructed phase space. The prominent advantage of this method is that it can avoid oscillations resulting from subjectivity and randomness when neighbor phase points are selected. Real photovoltaic power data are used to simulate the proposed model, and the results show that the proposed chaos model for photovoltaic power prediction can greatly improve the precision in power systems.**

***Index Terms*—photovoltaic power; Laguerre polynomials; information entropy; local chaos model**

I. Introduction

PHOTOVOLTAIC power generation produces variable output. Efficient prediction of photovoltaic power can help scheduling departments arrange and coordinate cooperation between conventional power and photovoltaic power generation, assist in making reasonable arrangements for power grid operation modes, improve the safety and stability of power system operations, contribute to the development of rational power field control strategies, minimize the adverse effects of solar variability on the power grid, and reduce the operational costs of power systems.[1], [2], [3]

In recent years, a large number of empirical studies have shown that photovoltaic power has chaotic behavior and unpredictable impacts on power system performance. Furthermore, the traditional model for photovoltaic power prediction cannot predict the evolutionary trend of power flow. Therefore, finding a flow prediction model and method that matches the chaotic characteristics of photovoltaic power generation is necessary[3].

Since the local chaos model is a good approximation for photovoltaic power generation, it has attracted increasing attention from researchers in the field of photovoltaic power prediction. Because the traditional local chaos model has slow convergence, incurs a large computational cost, and determines the fitted phase points and their weight according to the Euclidean distance, it displays poor performance in predicting photovoltaic power with high embedding dimensions[4]. To solve these problems, in this paper, a local chaos model based on the Laguerre polynomials and information entropy is proposed. The model combines the advantages of Laguerre polynomials and information entropy and can more accurately depict the dynamic behavior of photovoltaic power.

Manuscript received August 23, 2020; revised July 31, 2021. This work was supported by the Open Fund of the State Key Laboratory for Operation and Control of Renewable Energy and Storage Systems under Grant No. NYB51202001607 (China Electric Power Research Institute).

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II. Phase Space Reconstruction Theory

Chaotic behavior can appear to be random motion, and similar random behavior occurs in deterministic complex systems without the addition of any external factors[5], [6], [7], [8], [9], [10], [11]. The degree of chaos of a system can be measured by the maximum Lyapunov index λ. If $\lambda \geq 0$, then the system will appear to be chaotic.

Many complex factors can lead to the chaotic behavior of photovoltaic power. Because photovoltaic power data can be obtained through measurements obtained during the actual management of power systems, a method for restoring the geometry of the phase space of a chaotic data system from a known time series is needed. Takens' theorem in phase space reconstruction theory was proposed to solve this problem.

Takens' theorem states that for a known chaotic time series $\{x(k)\}_{k=1,2,\ldots,n}$, any delay time τ and an embedding space dimension $m \geq 2D_2 + 1$ (D_2 is the correlation dimension), we can find a smooth map $F : R^m \to R^m$ for the attractor such that $Y(t+1) = F[Y(t)]$, where $Y(t)$ is an m-dimensional vector and $Y(t) = [x(t), x(t+\tau), \ldots, x(t+(m-1)\tau)], t = 1, 2, \ldots, n-(m-1)\tau$.

Takens' theorem[8] laid a theoretical foundation for photovoltaic power prediction. The theorem indicates that the evolution trajectory of the reconstructed phase space of a chaotic time series is equivalent to the original chaos system in the sense of diffeomorphism, and the kinetic properties of the original system remain unchanged in the reconstructed phase space. By reconstructing the phase space, the limited system information can be used to explore the kinetic properties of the entire system.

According to the theorem, delay time τ can be determined with the autocorrelation function method[1], and embedding dimension m can be determined with the GP algorithm[3].

III. Laguerre Polynomials

In the interval $[0, \infty]$, the weight function $w(t) = e^{-x}$ constitutes orthogonal polynomials $L_n(x)(n = 0, 1, \ldots)$,

which are called Laguerre polynomials and are expressed as $L_n(x) = e^{-x}\frac{\mathrm{d}x}{\mathrm{d}x^n}(x^n e^{-x})$. Laguerre polynomials have the following key properties[12]:
(1) Recurrent relation:

$$\begin{cases} L_0(x) = 1, \\ L_1(x) = 1 - x, \\ L_{n+1}(x) = (1 + 2n - x)L_n(x), \\ -n^2 L_n - 1(x), n = 1, 2, \ldots. \end{cases}$$

The following expressions can be obtained:

$$\begin{aligned} &L_1(x) = 1, \\ &L_2(x) = x^2 - 4x + 2, \\ &L_3(x) = -x^3 + 9 * x^2 - 18x + 6, \\ &L_4(x) = x^4 - 16x^3 + 72x^2 - 96x + 24, \\ &L_5(x) = -x^5 + 25x^4 - 200x^3 + 600x^2 - 600x + 120. \end{aligned}$$

(2) Orthogonality:

$$(L_n, L_m) = \int_0^{+\infty} e^{-x} L_m(x) L_n(x)\,\mathrm{d}x = \begin{cases} 0, & m \neq n, \\ (n!)^2, & m = n. \end{cases}$$

(3) The best approximation[12], [13]: if $\{L_i(x)\}|_{i=0}^n$ is a polynomial sequence in interval $[a, b]$, then

$$\begin{aligned} \Phi &= span\{T_{0.}, T_{1.}, \ldots, T_{n.}\} \\ &= \{T(x)|T(x) = \sum_{k=0}^{n} a_k T_k(x), a_k \in R\}. \end{aligned}$$

If $f \in C[a, b]$ is a continuous function on interval $[a, b]$, then there exists a uniform approximation $T^* \in \Phi$ such that $||f - T^*|| = \inf_{T \in \Phi} ||f - T||$.

According to the above properties, Laguerre polynomials are orthogonal, converge quickly and have several excellent properties. From the point of view of a numerical approximation, applying several of these former items can allow the model to achieve high accuracy.

IV. Laguerre Polynomials and Local Chaos Model

A. Local Chaos Model

Suppose that the time series $\{x(j)\}_{j=1,2,\ldots,n}$ is known. To predict the time series, the phase space of the series is first reconstructed, and then, a local model is established for prediction. An appropriate delay time τ is selected and embedded into the phase space dimension, and the corresponding phase points of the reconstructed phase space can be obtained:

$$\begin{aligned} Y(1) &= [x(1), x(1 + \tau), \ldots, x(1 + (m - 1)\tau)], \\ Y(2) &= [x(2), x(2 + \tau), \ldots, x(2 + (m - 1)\tau)], \ldots, \\ Y(N) &= [x(N), x(N + \tau), \ldots, x(n)]. \end{aligned}$$

To predict $x(n + 1)$, only the phase points need to be predicted,

$$Y(N + 1) = [x(N + 1), x(N + 1 + \tau), \ldots, x(n + 1)].$$

Because $x(n + 1)$ is the last component, the key to predicting a time series is to obtain a good approximation of mapping F. Because chaotic behavior only exists in nonlinear circumstances, a nonlinear expression for F if obtained when fitting F. It is natural to consider polynomial fitting. According to Weierstrass approximation theory, any continuous function can be approximated through polynomial approximation in any small neighborhood domain with the desired accuracy.

The functional relationship between $Y(N+1)$ and $Y(N)$ can be approximately expressed with polynomials as follows:

$$\begin{aligned} Y(N + 1) &= F[Y(N)] \\ &= \alpha_0 + \alpha_1 Y(N) + \alpha_2 Y^2(N) + \cdots + \alpha_p Y^p(N). \end{aligned} \quad (1)$$

Model (1) is a polynomial local chaos model for chaotic time series. Some adjacent points of the predicted center $Y(N)$ are used as reference points for calculating the coefficients $\alpha_0, \alpha_1, \ldots, alpha_p$. Then, the historical data can be used to predict $Y(N + 1)$, thereby obtaining the predicted value of time series $x(n + 1)$. The above steps are repeated, and then, $x(n + 1)$ and $x(n + 2)$ are predicted through the phase space reconstruction technique to establish a chaos model for photovoltaic power prediction.

B. Laguerre Polynomial Model

When Model (1) has a high order p and a large number of samples, many calculations are required to calculate the coefficients $\alpha_0, \alpha_1, \ldots, \alpha_p$; if these coefficients have a high degree of correlation, then the prediction performance of the model will be affected. To eliminate these phenomena, in this paper, the good approximation effect, orthogonality and other good mathematical properties of Laguerre polynomials are utilized to establish a local prediction model.

Laguerre polynomial series $\{L_n(x), n = 0, 1, 2, \ldots\}$ is selected and used to replace the polynomial series $\{Y^n, n = 0, 1, 2, \ldots\}$ in Model (1); then, the following formula can be obtained:

$$\begin{aligned} &Y(N + 1) \\ &= \beta_0 + \beta_1 L_1[Y(N)] + \beta_2 L_2 Y(N) + \cdots + \beta_q L_q[Y(N)]. \end{aligned} \quad (2)$$

Model (2) is called the Laguerre polynomial local prediction model. The model coefficients $\beta_0, \beta_1, \ldots, \beta_q$ are calculated.

Suppose that $Y(k_1), Y(k_2), \ldots, Y(k_M)$ are M adjacent points of the predicted center $Y(N)$. According to Model (2), each adjacent phase point satisfies the following condition:

$$\begin{aligned} &Y(k_i + 1) \\ &= \beta_0 + \beta_1 T_1[Y(k_i)] + \beta_2 T_2 Y(k_i) + \cdots + \beta_q T_q[Y(k_i)], \\ &\qquad i = 1, 2, \ldots, M. \end{aligned} \quad (3)$$

Our aim is to obtain the predicted value of the last component of the phase point $Y(N + 1)$. When calculating the coefficients, we only need to consider the last component of each phase point. According to Model (3), the last component of each adjacent phase point satisfies the following condition:

$$\begin{aligned} &x(k_i + 1) \\ &= \beta_0 + \beta_1 L_j[x(k_i)] + \beta_2 L_j x(k_i) + \cdots + \beta_q L_j[x(k_i)], \\ &\qquad i = 1, 2, \ldots, M. \end{aligned} \quad (4)$$

Because $Y(k_1), Y(k_2), \ldots, Y(k_M)$ exert different effects on the predicted center $Y(N)$, we should consider this factor in the determination of the coefficients. Therefore, we first define the weight of each adjacent point. The traditional weighted local model can determine the adjacent phase point and the weight of the predicted center according to the Euclidean distance. When the embedding dimension of the reconstructed phase space is small, the distance parameter can basically reflect the correlation between the kinetic behaviors of the adjacent phase point and the predicted center. However, when the embedding dimension increases, the distance cannot objectively reflect their relationship[4], and the prediction effect of the model will be gradually reduced because it cannot be guaranteed that a point near the central point is on a track adjacent to the center point's track. Therefore, it cannot be guaranteed that the point exerts a large effect on the kinetic behavior of the predicted center, and a new method to identify an adjacent phase point and its weight must be found. This can improve the accuracy of the model in predicting a chaotic time series with a high embedding dimension.

V. Laguerre Polynomial Local Model Based on Information Entropy

A. Concept of Information Entropy

Entropy was originally a concept in thermodynamics[14]. After it was introduced into information theory, a wide variety of its applications in engineering technology, management science, social economy and other fields were discovered. In information theory, information entropy is a measure of the degree of disorder. If the information entropy is large, then the information has a high degree of disorder, and the information's utility value will be small. If the information entropy is small, then the degree of disorder is small, and the utility value of the information will be large. In a comprehensive evaluation, the use of entropy to evaluate the degree of disorder and utility value of information in an obtained information system is natural.

B. Establishment of the Model

To address the shortcomings of the traditional local model, in this paper, a weighted local linear model based on information entropy is proposed.

The concept of entropy can be used to explore the kinetic relationships between the predicted center $Y(N)$ and other phase points. In the evolution of $Y(N)$, the kinetic behavior is inevitably affected by other phase points $Y(1), Y(2), \ldots, Y(N-1)$. However, $Y(1), Y(2), \ldots, Y(N-1)$ exert different effects on the kinetics of the predicted center; thus, their contributions to fitting $Y(N+1)$ generally have different proportions. If the kinetic properties of a phase point are similar to those of the predicted center or if a certain phase point carries richer kinetic information than the predicted center, it will play a greater role in the fitting of $Y(N+1)$. Based on this idea, we can first consider defining the entropy of each phase point. The entropy value describes the amount of kinetic information in the predicted center contained by the adjacent phase points. Then, entropy is used to find the adjacent phase points of the predicted center, and the weight of each adjacent phase point is determined according to the entropy value. A new weighted local linear model is constructed to improve the low accuracy of the traditional weighted local linear model when predicting a chaotic time series with a high embedding dimension. First, the definition of adjacent phase points should be clarified. Here, an adjacent phase point refers to a phase point in the phase space for which the kinetic behavior and properties are very similar to the kinetic behavior and properties of the predicted center. That is, an adjacent phase point includes the kinetic information of the predicted center, and some kinetic characteristics of the predicted center can be deduced based on this information.

To facilitate description, the m components of each phase point in the phase space are renumbered. Suppose that

$$\begin{aligned} Y(1) &= [x(1), x(1+\tau), \ldots, x(1+(m-1)\tau)] \\ &= (x_{11}, x_{21}, \ldots, x_{m1}), \\ Y(2) &= [x(2), x(2+\tau), \ldots, x(2+(m-1)\tau)] \\ &= (x_{12}, x_{22}, \ldots, x_{m2}), \ldots \\ Y(N-1) &= [x(N-1), x(N-1+\tau), \ldots, x(n-1)] \\ &= (x_{1,N-1}, x_{2,N-1}, \ldots, x_{m,N-1}), \\ Y(N) &= [x(N), x(N+\tau), \ldots, x(n)] = (x_{1N}, x_{2N}, \ldots, x_{mN}). \end{aligned}$$

Then, $\delta_{1k} = |x_{1k} - x_{1N}|, \delta_{2k} = |x_{2k} - x_{2N}|, \ldots, \delta_{mk} = |x_{mk} - x_{mN}|, k = 1, 2, \ldots, N-1$.

The goal of searching for adjacent phase points is to understand the kinetic features of the predicted center according to the kinetic information obtained from the adjacent phase points. We focus on the amount of kinetic information from the predicted center carried by the adjacent phase points and select the adjacent phase points that contain the kinetic information of the predicted center in phase space. Therefore, the following decision matrix is constructed:

$$\triangle = \begin{bmatrix} \delta_{11} & \delta_{12} & \ldots & \delta_{1,N-1} \\ \delta_{21} & \delta_{22} & \ldots & \delta_{2,N-1} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{m1} & \delta_{m2} & \ldots & \delta_{m,N-1} \end{bmatrix}.$$

The matrix elements δ_{ij} represent the absolute deviation between the i^{th} component of phase point $Y(j)$ and the i^{th} component of predicted center $Y(N)$.

In phase space, the evolution of a phase point in orbit can be represented by its evolution in each component direction. Chaos theory[2] considers that the evolution of each component in a system is determined by the other components that interact with it, and the evolution of a single component in a kinetic system contains rich information. Therefore, by investigating the differences between the adjacent phase point and predicted center kinetic behaviors in each component direction of the phase point orbit, we can obtain the overall degree of similarity or dissimilarity between the kinetic properties of an adjacent phase point and the predicted center. A smaller δ_{ij} indicates that the kinetic behaviors of the i^{th} component of phase point $Y(j)$ and the i^{th} component of the predicted center $Y(N)$ have greater similarity in the orbit in phase space and that $Y(j)$ contains richer kinetic information of the predicted center $Y(N)$; when the kinetic information of the predicted center $Y(N)$ contained by $Y(k)$ is richer than that contained by $Y(l)$, $Y(k)$ has a stronger impact on the kinetic behavior of $Y(N)$ in that direction.

Suppose that $\delta_j^* = \min_i\{\delta_{ij}\}(j = 1, 2, \ldots, m)$; that is, δ_j^* is the minimum value of the j^{th} column and represents the absolute deviation of the lower limit of all of the components of phase point $Y(j)$ and the corresponding component of the predicted center $Y(N)$ on the evolution track corresponding to the j^{th} column. $D_{ij} = \frac{\delta_j^*}{\delta_{ij}}$ is used to represent the approximation of δ_{ij} and δ_j^*. D_{ij} is normalized and denoted by $d_{ij} = \frac{D_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{N-1} D_{ij}}$; then, D_{ij} is set, and the entropy value of phase point $Y(j)$ in the reconstructed phase space is defined as:

$$E_j = -\sum_{j=1}^{N-1} \frac{d_{ij}}{d_i} \ln \frac{d_{ij}}{d_i}.$$

According to the extremality of entropy, if the values of $\frac{d_{ij}}{d_i}$ are approximately equal, then the entropy will be large. If the values of $\frac{d_{ij}}{d_i}$ are exactly the same, then the value of entropy E_j reaches the maximum value: $\ln(N-1)$. It can be easily seen that if the absolute deviation between the component of each adjacent phase point $Y(j)$ and the corresponding component of the predicted center is small, that is, if each D_{ij} is close to 1, then the entropy E_j of $Y(j)$ will be large. Furthermore, the kinetic information of the predicted center contained by each component has a similar degree of variation; therefore, the kinetic information of the relevant predicted center provided by $Y(j)$ is relatively simple. If information entropy $E(j)$ of phase point $Y(j)$ is small, this indicates that the kinetic information of the predicted center contained in each component has a greater degree of variation and contains richer kinetic information of the relevant predicted center.

The adjacent points of the predicted center are determined according to the entropy value of each phase point, and the obtained adjacent points have the most kinetic information of the predicted center. In view of this, the entropy value is normalized, $e_j = \frac{1}{\ln(N-1)} E_j$ is obtained, and e_j is applied to supplement $q_j = 1 - e_j$.

Now, $q_j(j = 1, 2, \ldots, N-1)$ is used to determine the adjacent phase points of the predicted center $Y(N)$. Therefore, a certain value $q_{thr} \in (0, 1)$ is selected as the threshold, and q_j and q_{thr} are compared. If $q_j \geq q_{thr}$, then the corresponding phase point $Y(j)$ of q_j is used as an adjacent phase point of the predicted center $Y(N)$. Otherwise, it can be assumed that the kinetic properties of the phase point and the predicted center are too different and the phase point cannot be used as an adjacent phase point for fitting the evolution of the predicted center $Y(N)$. Using this approach, all of the adjacent phase points of the predicted center $Y(j_1), Y(j_2), \ldots, Y(j_M)$ are identified.

The weight of each adjacent phase point is defined as follows. The corresponding entropy value of the adjacent phase point $Y(j_k)(k = 1, 2, \ldots, M)$ is normalized and denoted by $q_k = 1 - e_k$. q_k is normalized, and the weight is obtained:

$$w_k = \frac{q_k}{\sum_{k=1}^{M} q_k}(k = 1, 2, \ldots, M).$$

Notably, $0 \leq w_k \leq 1$ and $\sum_{k=1}^{M} w_k = 1$ if $d_k = d_l$ (d_k and d_l represent the distances between the predicted center and adjacent phase points $Y(j_k)$ and $Y(j_l)$, respectively). However, $w_k \geq w_l$, indicating that the $Y(N)$ information contained by $Y(j_k)$ is much richer than that of $Y(j_l)$; thus, the impact of $Y(j_k)$ on the kinetic behavior of $Y(N)$ is much stronger than the impact of $Y(j_l)$ on the kinetic behavior of $Y(N)$.

Model (4) is a multivariate function of approximately $\alpha_0, \alpha_1, \ldots, \alpha_p$, and the weighted least squares method is used for calculation. The model is constructed to predict the sum of the squares of the errors:

$$\begin{aligned} e(\alpha_0, \alpha_1, \ldots, \alpha_p) = \sum_{i=1}^{M} w(k_i)\{x(k_i{+}1){-}\alpha_0{-}\alpha_1 L_1[x(k_i)] \\ - \alpha_2 L_2[x(k_i)] - \cdots - \alpha_p L_p[x(k_i)]\}^2, \end{aligned}$$

where $w(k_i)$ represents the weight of adjacent phase point $Y(k_i)$. According to the standards of the least squares method, coefficients $\alpha_0, \alpha_1, \ldots, \alpha_p$ should guarantee that $e(\alpha_0, \alpha_1, \ldots, \alpha_p)$ reach the minimum value; therefore, the partial derivatives of $\alpha_0, \alpha_1, \ldots, \alpha_p$ are calculated and set to zero:

$$\begin{aligned} \frac{\partial e}{\partial b_j} = 2\sum_{i=1}^{M} w(k_i)\{x({}_i{+}1){-}\sum_{m=0}^{p} \alpha_m L_m[x(k_i)]\} L_j[x(k_i)] \\ = 0, j = 0, 1, \ldots, q. \end{aligned}$$

After sorting, the following formula can be obtained:

$$\begin{aligned} \sum_{m=0}^{q} \beta_m \sum_{i=1}^{M} w(k_i) L_m[x(k_i)] L_j[x(k_i)] \\ = \sum_{i=1}^{M} w(k_i) x(k_i + 1) L_j[x(k_i)], j ==, 1, \ldots, q. \end{aligned}$$

After solving the equation, the coefficients in the model $\alpha_0, \alpha_1, \ldots, \alpha_p$ can be obtained. According to this prediction model, the predicted value of $Y(N+1)$ can be calculated, and the last component is taken from the predicted value to calculate the predicted value $x(n+1)$.

As observed from the entire modeling process, the model gives full consideration to the different contributions from the different adjacent phase points to the predicted center of the phase space and to the kinetic evolution process of $Y(N)$. It overcomes the shortcomings of the traditional weighted model, uses the distance as the basis to evaluate the prediction effect, and objectively describes the essential characteristics of the kinetic behavior of $Y(N)$. Therefore, it is a good nonlinear approximation function and can accurately predict the kinetic behavior of photovoltaic power.

VI. Numerical Simulation

In this section, we analyze the chaotic behavior and characteristics of actual photovoltaic power. Based on this, we validate the effectiveness of our prediction model through numerical simulations.

The data used for the numerical simulations are selected from 1213 samples of photovoltaic power data provided by an electricity institute[12], and the time series $x(1), x(2)m \ldots, x(1213)$ is constructed. As shown in Fig. 1, these data are used to establish a local chaos model to predict the evolution trend of photovoltaic power and verify the prediction effect of the model.

A. Analysis of the Chaotic Behavior and Characteristics of Photovoltaic Power

We adopt a power and attractor phase diagram and perform qualitative analysis to determine whether the flow series have chaotic characteristics.

By analyzing the power spectrum of photovoltaic data, we can intuitively determine whether a series has the chaotic form of a power system and determine whether the power spectrum of a chaos data series has continuity, noisy background features and broad peak features. Fig. 2 shows the power spectrum of the photovoltaic data, and it is characterized by continuity, noisy backgrounds and broad peaks. These are the characteristics of the chaotic motion of photovoltaic power. On the logarithmic scale, the power spectrum at low frequencies decreases according to the rules of a power function, which is also an external manifestation of the chaotic characteristics of photovoltaic power.

A three-dimensional phase diagram is used to display the attractors of photovoltaic power, as shown in Fig. 3. Attractor orbits gather together in phase space and have rough and irregular geometries. This result reflects the kinetic properties of the chaotic photovoltaic power system from another perspective.

Then, the Lyapunov index λ of the photovoltaic power is calculated. First, the sequence is reconstructed in phase space. This process requires two important parameters, namely, embedding dimension m and delay time τ. We use the autocorrelation function method[15], [16], [17], [18] to determine the value of τ, as shown in Fig. 4. The abscissa is the delay time, and the Y-axis is the autocorrelation function of the photovoltaic power series. τ, which can reduce the autocorrelation function value to $1 - \frac{1}{e}$, is the delay time, and the value of τ is 10. The Cao algorithm can be used to calculate m, as shown in Figure 5. The abscissa is the embedding dimension, and the Y-axis shows the values of E1 and E2. The value of m that enables the E1 and E2 curves to approach each other is the required embedding dimension, and after calculation, we find that m=8.

After obtaining embedding dimension m and delay time τ, we can use small data sets to calculate the Lyapunov index λ. As shown in Fig. 6, the slope of the linear portion of λ is calculated and is greater than zero. The results indicate that the movement of the photovoltaic power has chaotic characteristics, which is consistent with previous results based on the analyses of power and attractor geometry. Therefore, we will use the proposed local chaos model to predict the photovoltaic power.

B. Prediction of Photovoltaic Power

The phase space of the photovoltaic power series is reconstructed, and 964 phase points are obtained, of which the $Y(964)$ predicted center takes its adjacent phase point as the reference fitting point. The order q of Chebyshev polynomials is set to 2 and 3 to establish the corresponding local prediction model. To compare the prediction effects, we adopt the local chaos model based on the traditional Euclidean distance to predict the photovoltaic power.

To evaluate the prediction effect of the model, $\bar{x}(t)$ and $\hat{x}(t)$ are set as the mean value and predicted value of the series. The relative error is defined as

$$E = \frac{|x(t) - \hat{x}(t)|}{|x(t)|}.$$

In addition, the regularization mean square error is

$$MSE = \frac{\sqrt{\sum_{t=1}^{N} [x(t) - \hat{x}(t)]^2}}{\sqrt{\sum_{t=1}^{N} [x(t) - \bar{x}(t)]^2}}.$$

The prediction effects are shown in Fig. 7. It can be easily observed that the prediction effect of each model is relatively close to the actual photovoltaic power. Table 1 shows the average relative errors. Notably, from the perspective of the relative error, the new model has better prediction performance.

Table 2 shows the mean square error of each prediction model. Compared with the traditional model, the first-order and second-order Laguerre polynomial models exhibit significantly improved prediction accuracy; the prediction effect of the second-order model is much better than that of the first-order model. This indicates that a second-order orthogonal local model can achieve good approximation results for the flow series.

TABLE I
AVERAGE RELATIVE ERRORS OF EACH PREDICTION MODEL.

Model	Traditional	1st-order	2nd-order
Errors	0.2849	0.2024	0.1616

TABLE II
MEAN SQUARE ERROR OF EACH PREDICTION MODEL.

Model	Traditional	1st-order	2nd-order
MSE	0.331	0.225	0.216

VII. CONCLUSION

Photovoltaic power predictions can improve the ability to adjust a power grid peak, the ability to incorporate photovoltaic power, the safety and stability of power grid operation, and the competitiveness and risk avoidance of power generation companies. The establishment of a photovoltaic power prediction system can provide strong technical support for the power grid and can provide significant economic and social benefits for investment enterprises and other institutions. In this paper, a weighted local linear model for photovoltaic power prediction based on Laguerre polynomials and information entropy is proposed. The model exploits the good approximation effect of Laguerre polynomials and considers the impact of adjacent phase point information entropy on the kinetic behavior of the predicted center, thus significantly improving the photovoltaic power prediction effect.

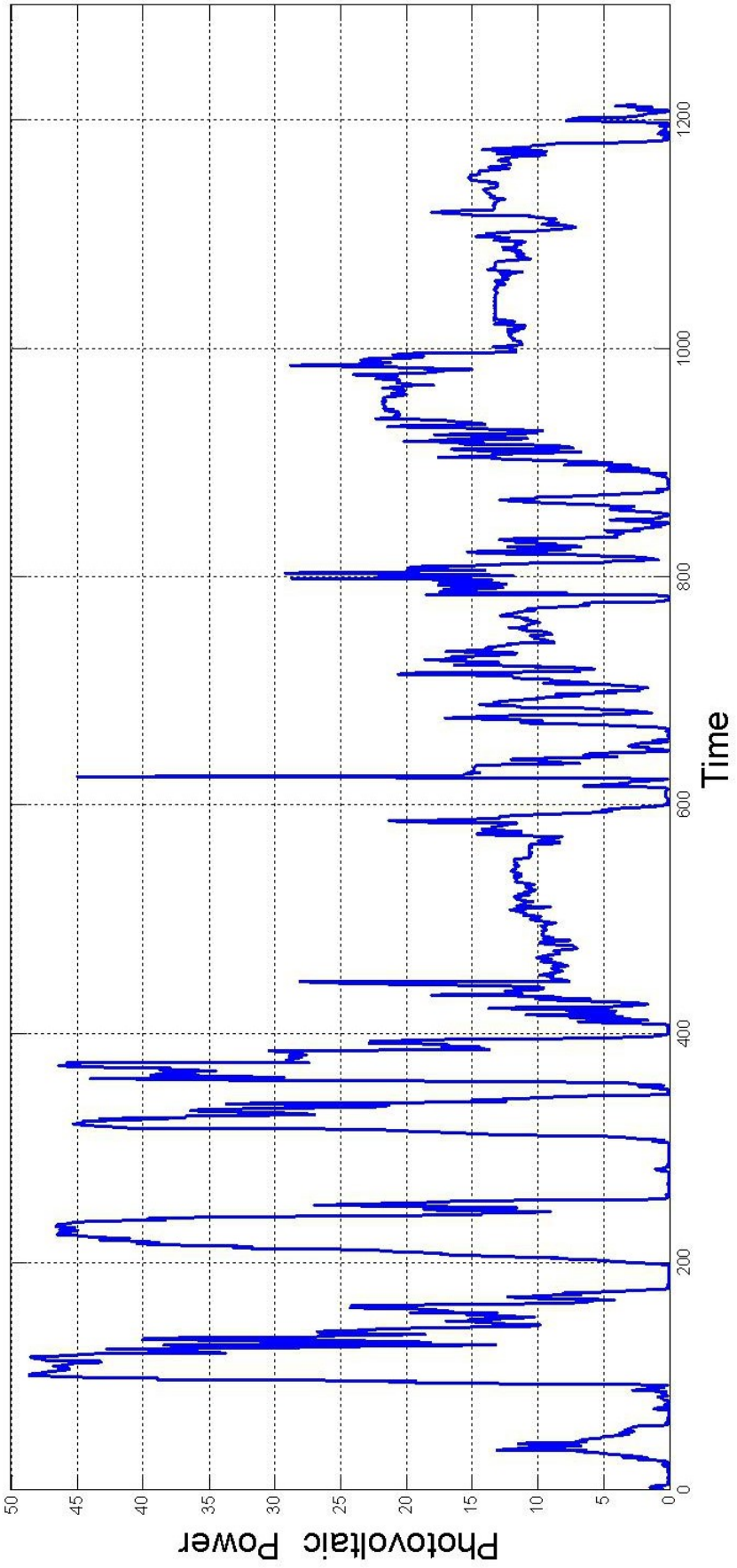

Fig. 1. Photovoltaic Power Series.

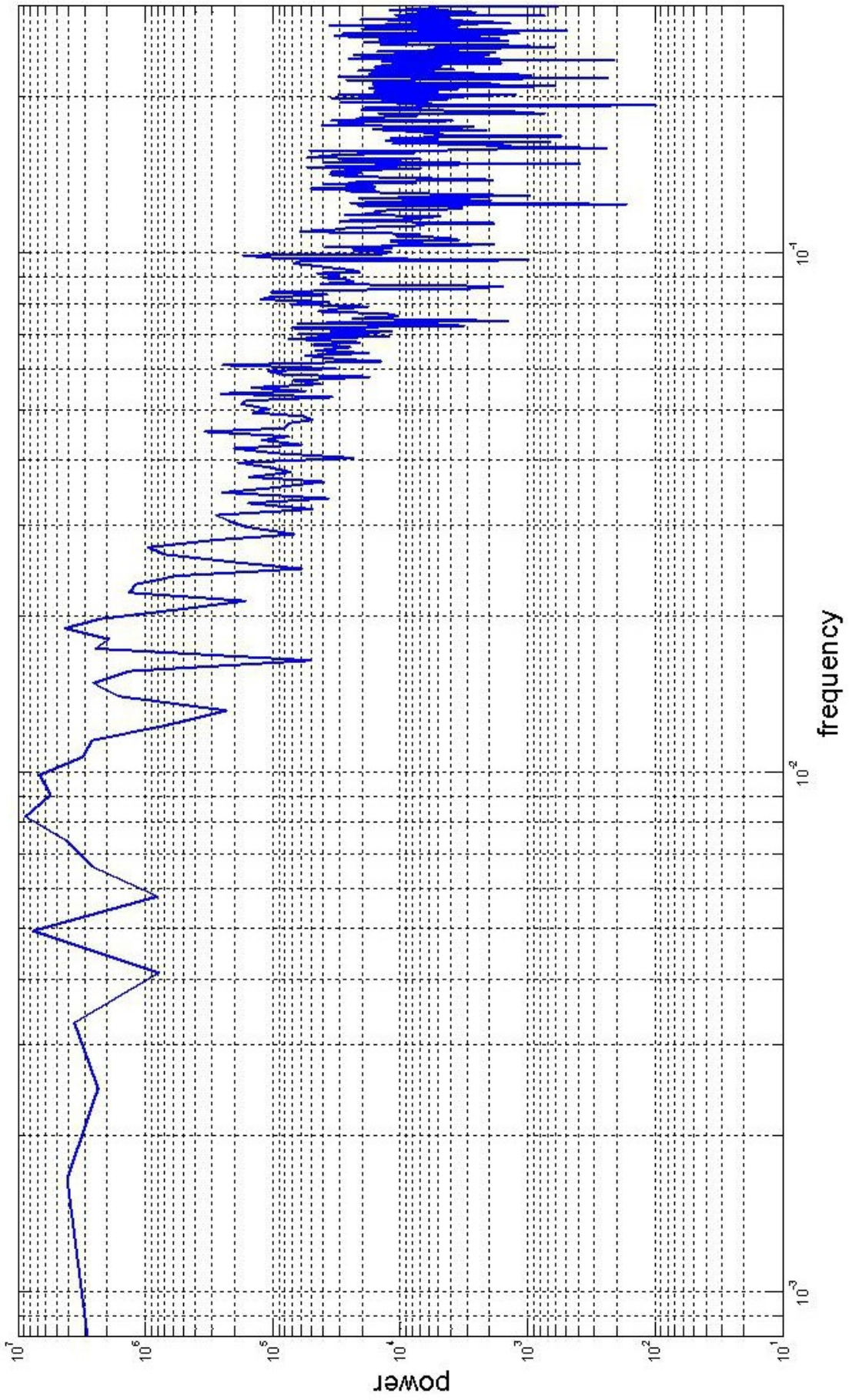

Fig. 2. Power Spectrum.

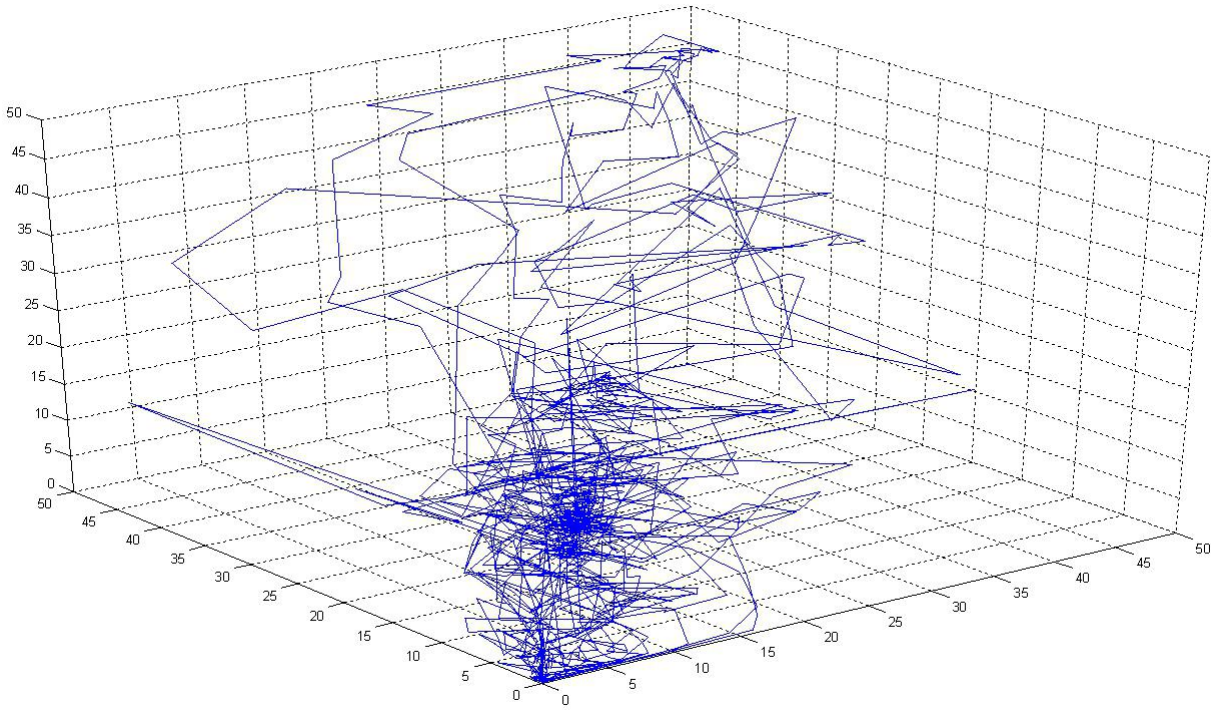

Fig. 3. Attractor Phase Diagram.

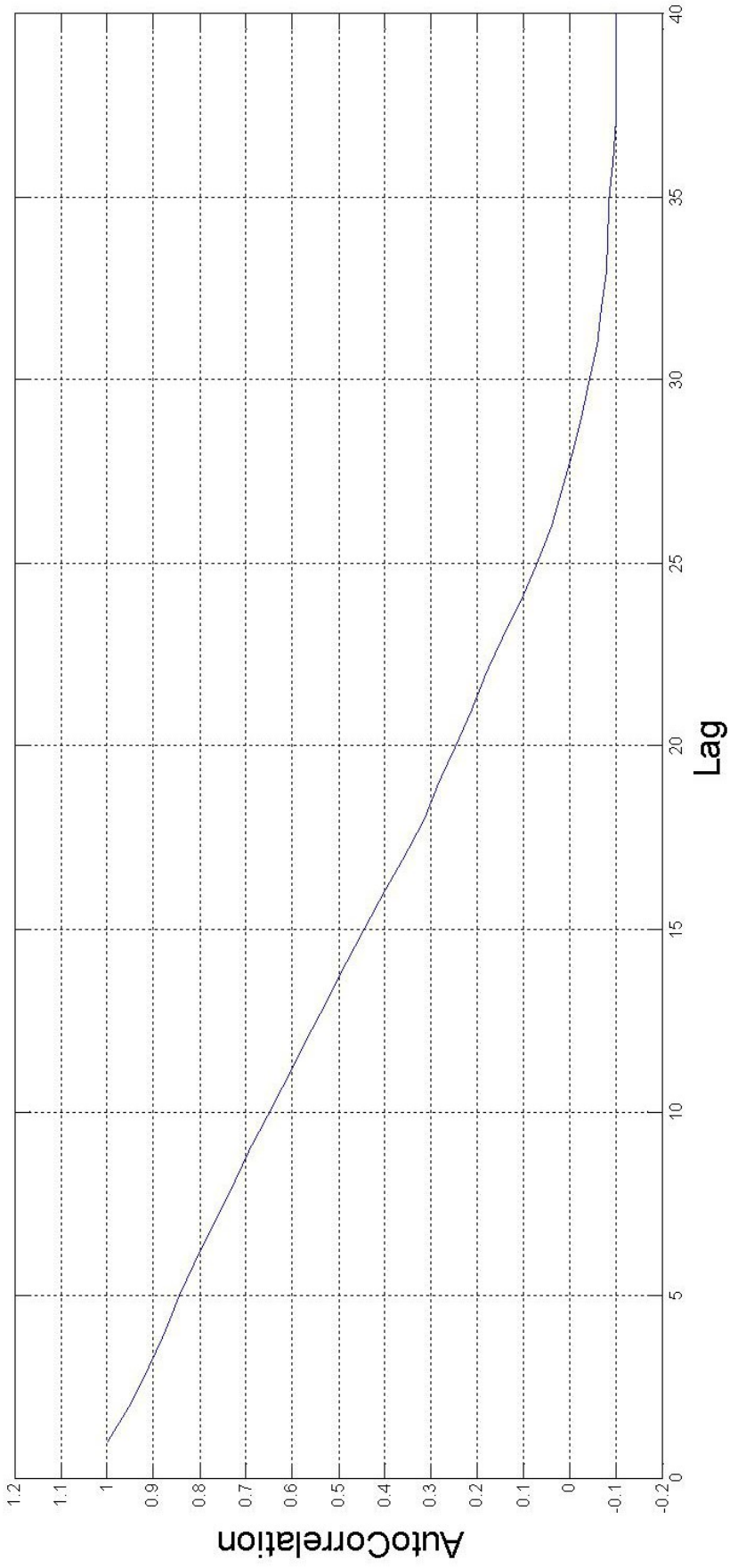

Fig. 4. Delay Time.

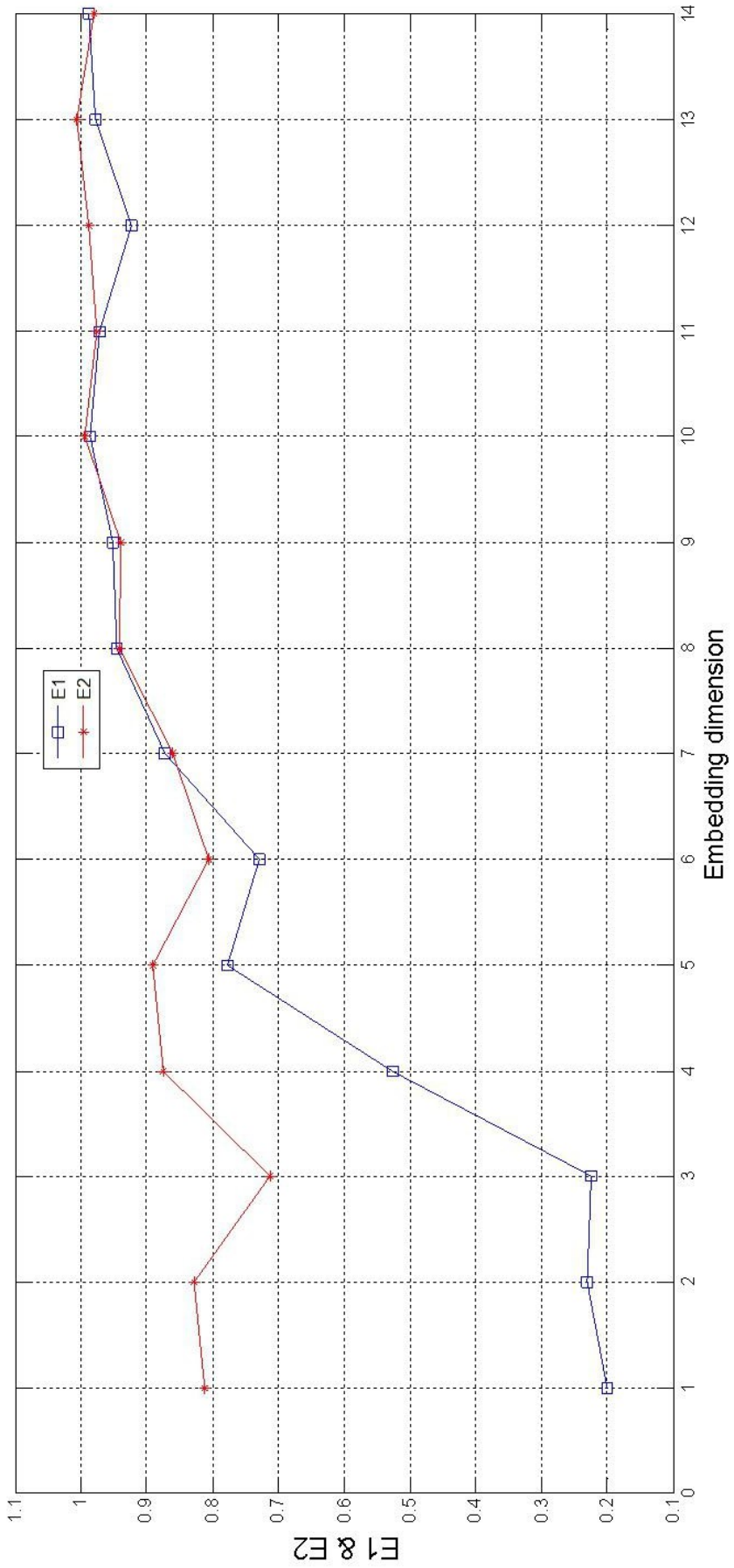

Fig. 5. Embedding Dimension.

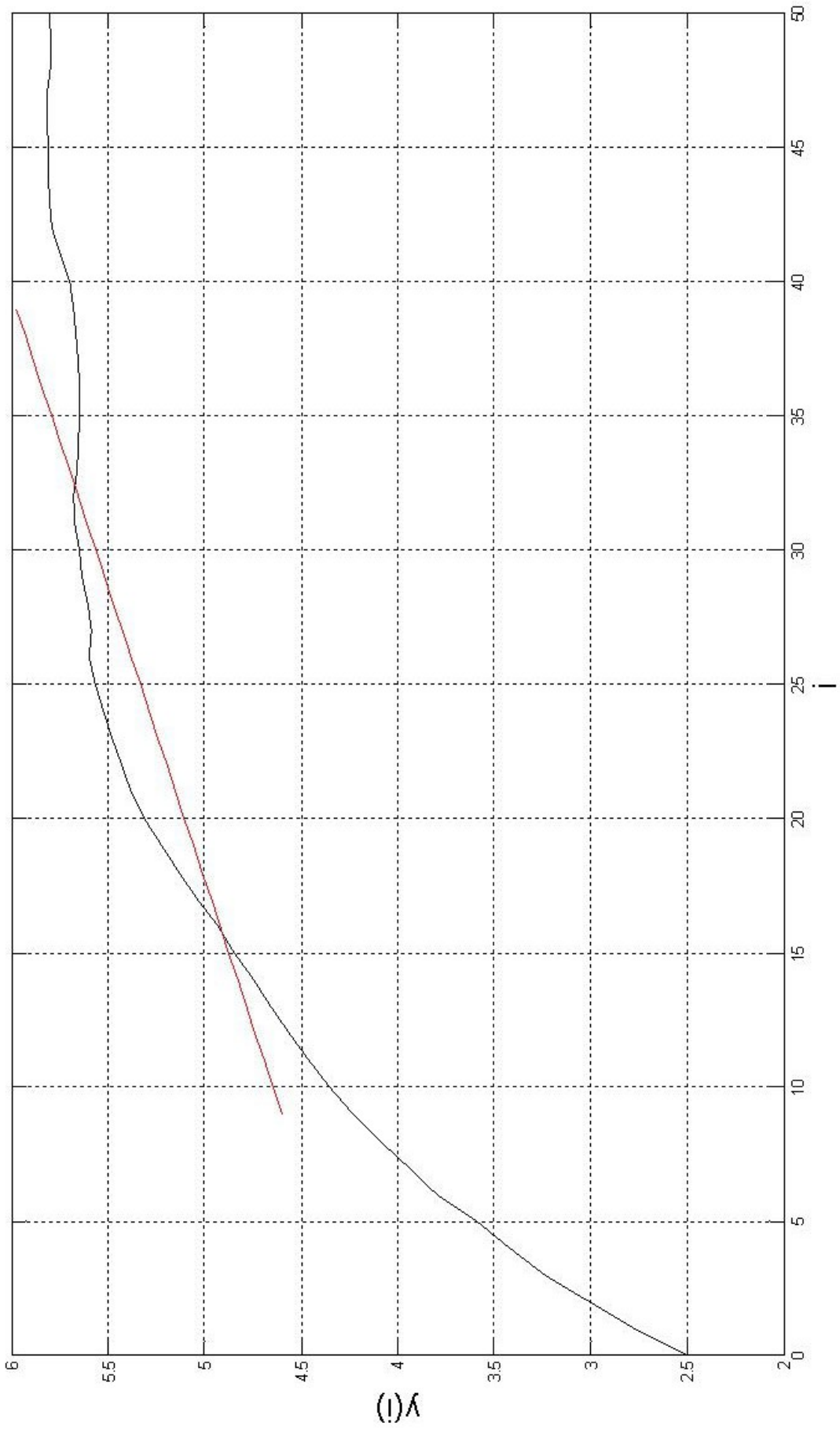

Fig. 6. Lyapunov Index.

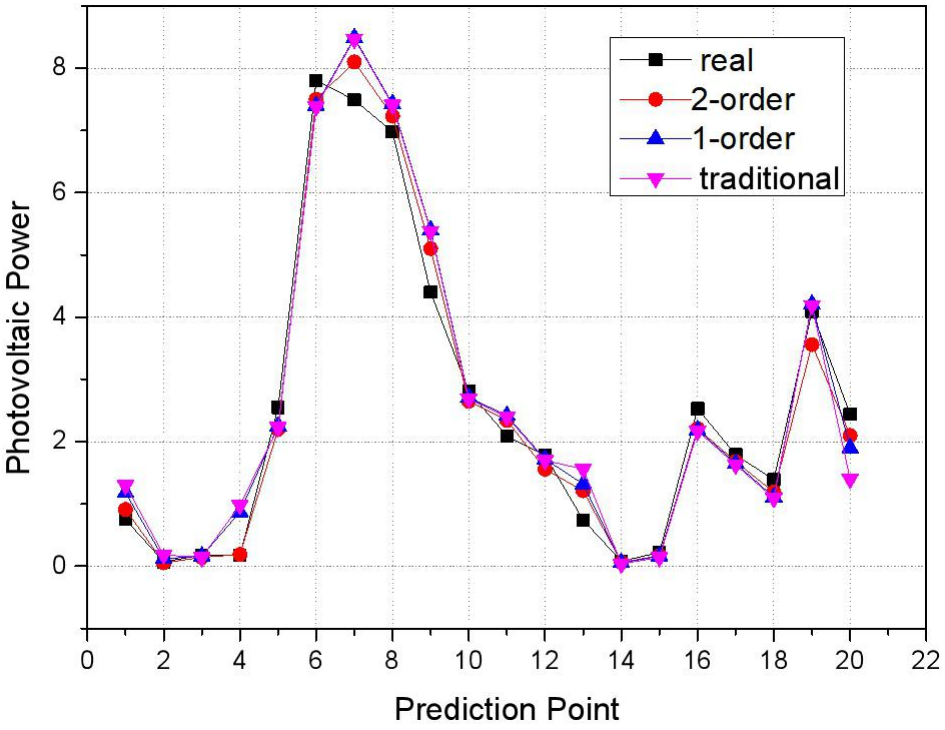

Fig. 7. Comparison of the Prediction Effects of the Models.

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