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Winder Power Prediction Utilizing Manifold Learning Dimensional Reduction Method and Elman Neural Network

Ruili Zhang[1,2]

[1]Department of Computer and Information Engineering, Heze University, Heze 274015, Shandong, China
[2]Key Laboratory of computer Information Processing, Heze University, Heze 274015, Shandong, China
hzxy_zrl@163.com

Abstract

Wind power prediction has become a hotspot in recent years. The parameters relevant to the wind power are considerable and complexity. Dimension reduction has become another hotspot. The traditional methods utilize linear methods to reduce the dimension of measured data. However, data that located in high-dimensional space often have nonlinear structure. So, we consider the original data present manifold structures and introduce manifold learning methods to extract the important information. In this paper, we utilize LLE algorithm and Elman neural network to establish the wind power prediction model. The experiment results demonstrate the excellence of our method. Finally, we chose different algorithm parameters to complete the experiments and got the roughly optimal parameters. In addition, our method can be applied to similar fields.

Keywords: *Wind Power; Dimension Reduction; Manifold Learning; LLE Algorithm; Elman Neural Network*

1. Introduction

Wind energy is a clean, inexhaustible energy. With the development of wind power technology, the world wind power capacity is rapidly growing. Since the power output of wind farms with volatility and uncertainty, large-scale wind power connected to the electricity market and power grid dispatching a huge challenge [1]. Wind power prediction is considered to be an important means to solve this problem [2, 3]. Therefore, the research and application of wind power forecasting has been rapid development, forecasting methods continue to improve, continue to improve prediction accuracy. However, due to the inherent randomly of wind, the wind farm output power is still difficult to accurately predict.

Existing wind farm power output prediction methods can be divided into two types, physical methods and statistical methods [4]. Physical methods require the physical characteristics of the atmosphere and an accurate mathematical model to describe the wind farm features. It will bring a great impact on forecast results if the model is not careful. Compare with the physical predictive models, statistical models are more simply than it and thus become the focus of current research.

In practical applications, there exist many parameters relevant to the wind power such as wind speed, air pressure and humidity. In addition, we have a number of instruments were used to measure the results. Enter all of them into the prediction model is cumbersome. So, we need to extract the most useful information from them.

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Many researchers using conventional methods to process these parameters such as PCA *etc*. [5-7] But there exists an obvious shortage which the data located in high-dimensional space often have complexity nonlinear structures. To solve this problem and enhance the prediction performance, we introduce manifold learning methods to reduce the high-dimensional original data [8-10].

The paper is organized as follows: In Section 2, we briefly the method of manifold learning of dimensional reduction and the most classic manifold learning method called Locally Linear Embedding (LLE) [11- 14]. In Section 3, we introduce the Elman neural network and utilize the low-dimensional data to establish the wind power prediction model. In Section 4, we construct the prediction experiment on a set of measured data. Then, we analyzed the parameters sensitivity seriously. Section 5 contains the conclusions and further studies.

2. Manifold Learning for Dimensional Reduction

2.1. Manifold Learning Methods

Manifold learning method has become a hot research topic in the field of machine learning in recent years. Especially in 2000, LLE, Isomap and some other classic manifold learning methods [15-17] were presented on "Science", manifold learning methods received widespread attention. After a dozen years of further development, many new popular learning methods have also been proposed, such as LSTA, LEM, *etc*. In many important international meetings, manifold learning has become a call for papers as an important keyword. In the application, manifold learning in computer vision, data mining, information retrieval and other areas have shown a good performance.

One of the most important algorithms is Locally Linear Embedding (LLE). The algorithm utilize the local linear relationship to characterize all the nonlinear high-dimensional data structure, each data point is represented as a weighted linear combination of the neighboring points, thus solving the matrix reconstructed by the low-dimensional representation of the data. Advantage of this algorithm is that there is an optimal solution, computing more efficient, you can solve the problem of high-dimensional data, and can best maintain high data local neighborhood relations in a low dimensional embedding space. The disadvantage is that the overall structure will cause deformation, and when the spherical cavity or exists a closed area data, the algorithm is unstable.

2.2. Locally Linear Embedding

Cause Locally Linear Embedding (LLE) algorithm bases on a simple and effective model and showing a good performance during the processing of nonlinear data. It has been widely used in machine learning, image processing, pattern recognition, computer vision and other fields. LLE is a classic nonlinear manifold learning method; it can keep the original topology of the original data after date dimensionality reduction as shown in Figure 1.

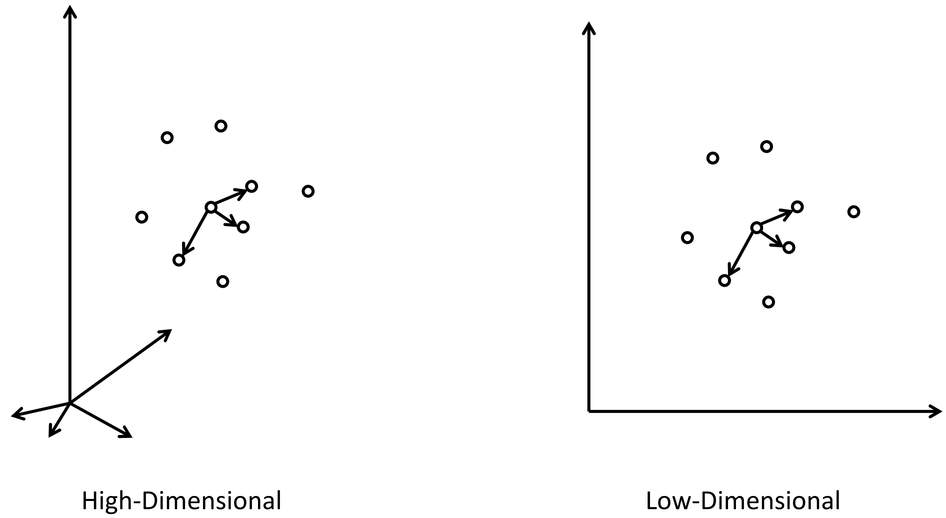

Figure 1. Illustration of LLE Algorithm

The processing of LLE is detail as follows briefly:

Firstly, find the k-nearest points of each sample point in high-dimensional space as the neighborhoods.

Secondly, calculate the partial reconstruction matrix and reconstruct the data points utilizing the neighborhoods. The error function is as follow:

$$e = \sum \left| X - \sum_{j=1}^{k} W X_j \right|^2 \tag{1}$$

Finally, embed the original high-dimensional data in low-dimensional space utilizing the reconstruction matrix. The error function is as follow:

$$e = \sum \left| Y - \sum_{j=1}^{k} W Y_j \right|^2 \tag{2}$$

We can find that the difference between the two error functions is the high-dimensional data X and low-dimensional data Y. That means LLE can keep the locally linear structure of original data.

The advantages of this algorithm are that there is an optimal solution and computing more efficient. LLE algorithm can solve the problem of high-dimensional data, and can maintain the optimal relationship between the local neighboring data in a high-low dimensional embedding space, but because of the low dimensional embedding data covariance normalization constraint, will cause deformation of the overall structure. The disadvantage is that since the distance relationship is not a low dimensional embedding LLE data held between, and thus makes the overall deformation, and when the spherical cavity and a closed area data exists, the algorithm is unstable.

3. Elman Neural Network Prediction

3.1. Elman Neural Network

Elman neural network is first proposed by professor J. L. Elman and applied in speech processing problems in 1990 [18, 19, 20]. It is a typical local regression network. Elman neural network can be seen as a forward neural network (BP Neural Network) with local memory units and local feedback connections. Elman network has a similar structure with multilayer feed forward networks. Its main structure contains feed forward connection, input layer, hidden layer and output layer.

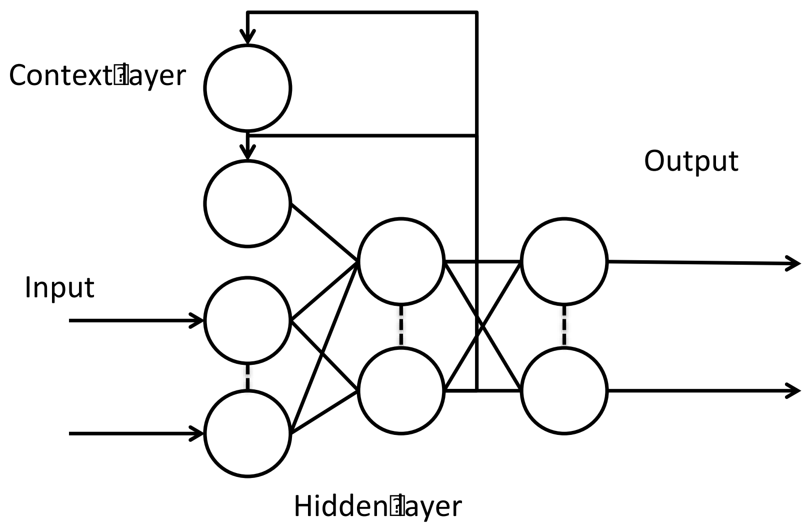

Figure2. Structure of Elman Neural Network

Elman neural network regression model are generally divided into four layers: input layer, hidden layer, context layer and output layer, as shown in Figure 2. Its input layer, hidden layer and output layer are similar to the feed forward network. Connection in units of input layer only play the role of signal transmission, the output layer units' role is to calculate the linear weighted effect. The transfer function of the hidden layer units can be a linear or nonlinear function. Context layer is used to output the value of the implicit memory layer of the previous time unit, can be considered a step delay operator.

Elman neural network's character is linked to the input from the hidden layer to output by a structural unit of the delay, storage, and this self-associative data was sensitive to the history of the state. The adding internal feedback network increasing the capacity of the network itself to deal with dynamic information and can help modeling dynamic processes. In addition Elman dynamic characteristics of the network provided only by internal connections without using the state as an input signal or training, which is Elman network's strengths relative to the static feed forward networks.

3.2. Prediction Model

After we get the embedding data, we establish the prediction model utilizing Elman neural network. We select the first part of the data as the training samples and the rest as test samples.

In order to better demonstrate the algorithm, the flow diagram of our prediction method is shown in Figure 3.

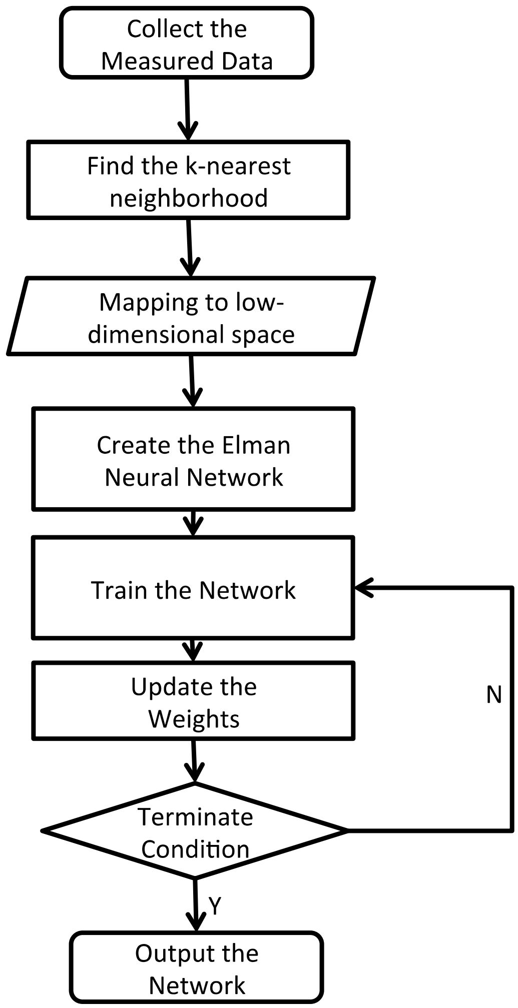

Figure 3. Diagram of Our Prediction Method

4. Experimental Results

We choose a set of measured data form a wind farm as the experimental samples, wherein, there exist near thirty parameters. Firstly, we utilize LLE algorithm to reduce the high-dimensional data. Then, the embedding data are input to the Elman neural network to predict the wind power.

However, the parameters k-neighborhood and d-dimensional have great influences on the prediction results. In order to exhibit our model, the experiments are divided into three parts:

1. Directly use original data with Elman network to predict the wind power.

2. Select different values of d to embedding the original data to low-dimensional space. Then, calculate and compare the precision of them.

3. Select different values of k to construct the locally linear structure with a fixed value of d-dimensional. Then, utilize the embedding data to predict the wind power.

Firstly, we directly utilize the original data to predict the wind power, the results are shown in Figure 4.

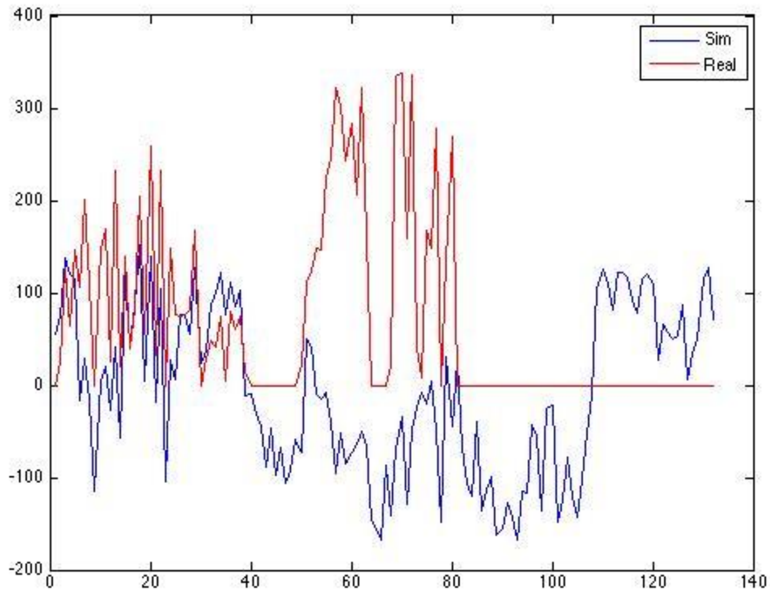

Figure 4. Prediction Results by Exploiting the Original Data

Obviously, the prediction results are undesirable and have a large error cause there are too many noises in the original data. Then, we reduce the data dimensional exploiting LLE algorithm and train the Elman neural network.

We select different dimensions and reconstruct the prediction model and calculate their prediction errors respectively as shown in Table 1.

Table 1. Precession of Different Dimensions

d-dimensional	Prediction Error
28	2784526.06683963
2	1375830.51293654
3	1324380.24945020
4	1631621.84718050
5	1421156.74431436
6	2194397.67246581

From Table 1 we can clearly find that the 3-dimensional embedding data reached the highest precision. In order to reveal the dimensionality reduction results. We drawn the distribution map of the embedding data in Figure 5.

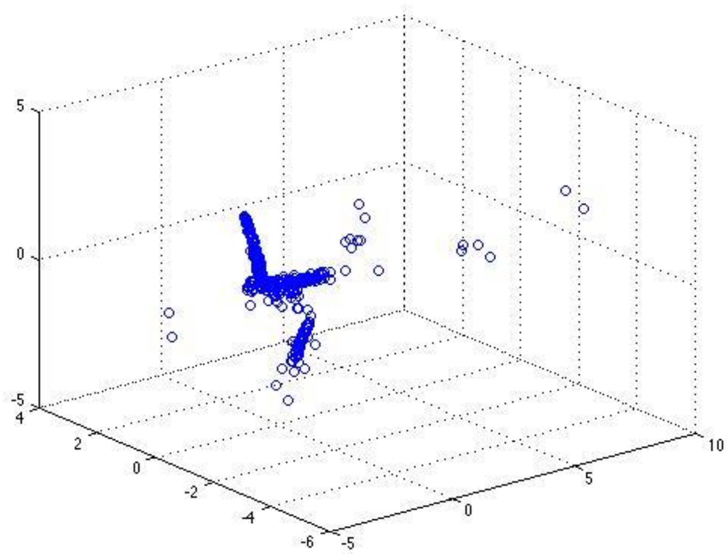

Figure 5. Mapping Original Data to 3-dimensional Space

In Figure 5, data are separated and have great distinction. This shows that the dimensionality reduction algorithm is effective.

Finally, we select different values of k-nearest as neighborhoods. Then, we recalculate the prediction errors as shown in Table 2.

Table 2. Precession of Different k-nearest

k-nearest	Prediction Error
28	2784526.06683963
5	4885029.43007419
10	797192.87733990
20	125950.62789771
30	1324380.24945020
40	2288198.97131478

From Table 2 we can clearly find that when k = 10, the algorithm reached the highest accuracy. Figure 6 shows the prediction results.

Compare with Figure 4, the prediction precision has an excellent improvement. This illustrates the data dimensionality reduction method is applied to this problem is very effective, but also shows the manifold learning method is an effective means to reduce the dimension of high-dimensional data. In addition, our method can be applied in related areas.

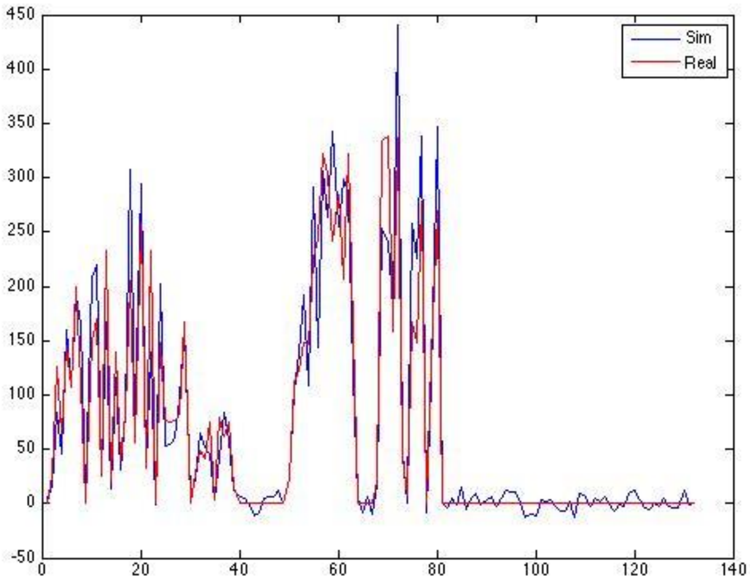

Figure 6. Prediction Results by Exploiting the Embedding Data

5. Conclusion

In this paper, we introduce manifold learning method to reduce the dimensions of high-dimensional original measured data. It resume the data are located in a high-dimensional nonlinear space. So, it can solve the theoretical shortcomings of traditional methods such as PCA and MDS. Then, we utilize Elman neural network to predict the wind power data by utilizing the embedding data. However, there still exist many problems on wind power prediction need to study.

Further works are focus on two aspects: (i) how to accuracy select the two parameters k-nearest and d-dimensional previously; (ii) mining the relationship between the embedding data and original data to better elaborate the significant of dimensional reduction. In addition, further work will consider more complexity data and problems.

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References

[1] H. Holttinen, P. Meibom and A. Orths, "Impacts of Large Amounts of Wind Power on Design and Operation of Power Systems, results of IEA collaboration", Wind Energy, vol.14, no. 2, **(2011)**, pp. 179-192.
[2] L. Zhang, T. Ye and Y. Xin, "Problems and Measures of Power Grid Accommodating Large Scale Wind Power", Proceedings of the CSEE, vol. 30, no. 25, **(2010)**, pp. 1-9.
[3] M. G. De Giorgi, A. Ficarella and M. Tarantino, "Error analysis of short term wind power prediction models", Applied Energy, vol. 88, no. 4, **(2011)**, pp. 1298-1311.
[4] R. Levy and H. McGinness, "Wind Power Prediction Models", NASA STI/Recon Technical Report N, vol. 77, **(1976)**, pp. 12509.

[5] A. Kusiak, H. Zheng and Z. Song, "Wind farm power prediction: a data- mining approach", Wind Energy, vol. 12, no. 3, **(2009)**, pp. 275-293.
[6] I. J. Ramirez-Rosado, L. A. Fernandez-Jimenez and C. Monteiro, "Comparison of two new short-term wind-power forecasting systems", Renewable Energy, vol. 34, no. 7, **(2009)**, pp. 1848-1854.
[7] D. J. Sailor, M. Smith and M. Hart, "Climate change implications for wind power resources in the Northwest United States", Renewable Energy, vol. 33, no. 11, **(2008)**, pp. 2393-2406.
[8] C. Bregler and S. M. Omohundro, "Nonlinear manifold learning for visual speech recognition //Computer Vision", Proceedings Fifth International Conference on. IEEE, **(1995)**, pp. 494-499.
[9] C. Bregler and S. M. Omohundro, "Nonlinear manifold learning for visual speech recognition //Computer Vision", Fifth International Conference on. IEEE, **(1995)**, pp. 494-499.
[10] M. H. C. Law, A. K. Jain, "Incremental nonlinear dimensionality reduction by manifold learning", Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 28, no. 3, **(2006)**, pp. 377-391.
[11] S. T. Roweis and L. K. Saul, "Nonlinear dimensionality reduction by locally linear embedding", Science, vol. 290 (5500), **(2000)**, pp. 2323-2326.
[12] D. L. Donoho, C. Grimes, "Hessian eigenmaps: Locally linear embedding techniques for high-dimensional data", Proceedings of the National Academy of Sciences, vol. 100, no. 10, **(2003)**, pp. 5591-5596.
[13] D. de Ridder and R. P. W. Duin, "Locally linear embedding for classification", Pattern Recognition Group, Dept. of Imaging Science & Technology, Delft University of Technology, Delft, The Netherlands, Tech. Rep. PH-2002-01, **(2002)**, pp. 1-12.
[14] Q. Yan, D. Liang and D. Zhang, "Recognition of weed in corn field based on supervised locally linear embedding algorithm", Transactions of the Chinese Society of Agricultural Engineering, vol. 29, no. 14, **(2013)**, pp. 171-177.
[15] M. Balasubramanian and E. L. Schwartz, "The isomap algorithm and topological stability", Science, vol. 295, no. 5552, **(2002)**, pp. 7-7.
[16] J. A. Lee, A. Lendasse and M. Verleysen, "Nonlinear projection with curvilinear distances: Isomap versus curvilinear distance analysis", Neurocomputing, vol. 57, **(2004)**, pp. 49-76.
[17] T. Zhang, J. Yang and D. Zhao, "Linear local tangent space alignment and application to face recognition", Neurocomputing, vol. 70, no. 7, **(2007)**, pp. 1547-1553.
[18] J. L. Elman, "Finding structure in time", Cognitive science, vol. 14, no. 2, **(1990)**, pp. 179-211.
[19] R. S. Toqeer and N. S. Bayindir, "Speed estimation of an induction motor using Elman neural network", Neurocomputing, vol. 55, no. 3, **(2003)**, pp. 727-730.
[20] F. J. Lin, Y. C. Hung and S. Y. Chen, "FPGA-based computed force control system using Elman neural network for linear ultrasonic motor", Industrial Electronics, IEEE Transactions, vol. 56, no. 4, **(2009)**, pp. 1238-1253.

Author

Ruili Zhang was born in 1980 at Shandong heze, and received the Master of computer application technology from the "Changchun University of Technology" in 2009. He is now a assistant of the Department of Computer and Information Engineering, Heze University. Her research interests include the data mining, Artificial intelligence.