IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received June 12, 2019, accepted July 1, 2019, date of publication July 5, 2019, date of current version August 12, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2926986

A Fast Algorithm for Network Forecasting Time Series

FAN LIU[1] AND YONG DENG[2]
[1]Yingcai Honors of School and School of Mathematical Sciences, University of Electronic Science and Technology of China, Chengdu 610054, China
[2]Institute of Fundamental and Frontier Science, University of Electronic Science and Technology of China, Chengdu 610054, China

Corresponding author: Yong Deng (dengentropy@uestc.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61573290 and Grant 61503237.

ABSTRACT Time series has a wide range of applications in various fields. Recently, a new math tool, named as visibility graph, is developed to transform the time series into complex networks. One shortcoming of the existing network-based time series prediction methods is time consuming. To address this issue, this paper proposes a new prediction algorithm based on visibility graph and Markov chains. Among the existing network-based time series prediction methods, the main step is to determine the similarity degree between two nodes based on link prediction algorithm. A new similarity measure between two nodes is presented without the iteration process in the classical link prediction algorithm. The experiments show that the proposed method has better accuracy with less time consuming.

INDEX TERMS Time series, visibility graph, Markov chains, similarity measure, link prediction, construct cost index.

I. INTRODUCTION

Time series analysis and prediction is an important topic which is used in the fields of traffic [1], finance [2], engineering [3]–[5], complex networks [6]–[9], and so on [10]–[15]. Time series analysis can help analyze the characteristics of data and explore potential information [16]–[18]. For example, predicting project costs can help individuals and organizations reduce costs and schedule projects. Construction cost index (CCI) is the weighted sum of the average price of labor, standard structural steel, Portland cement, and wood, which is widely used in housing construction [19].

There are a lot of traditional time series foresting methods including the stochastic [20], support vector machines (SVM) [21] and neural network methods [22]. Autoregressive Integrated Moving Average (ARIMA) [20] is a typical method in stochastic methods. ARIMA has several types, such as Autoregressive Moving Average (ARMA) [23]–[25], Autoregressive (AR) [26]–[28]. Moving Average (MA) [23], [24], [29]. Neural Network [20], [22], [30] is a data-driven approach. SVM [31], [32] has many applications in time series, such as regression, signal processing, and time series analysis.

The associate editor coordinating the review of this manuscript and approving it for publication was Dominik Strzalka.

The real world is fulled with uncertainty [33]–[35]. One main reason is that the interaction between each fact in the complex system can not only be modeled in a precise way [36]–[39] but also the knowledge of the system is incomplete [40], [41]. Many methods are presented to handle uncertainty in time series prediction such as gray analysis [42], [43]. The typical work is to predict time series with fuzzy sets theory [44] due to its efficiency to deal with linguistic variables [45]–[48]. However, It's necessary to develop more efficient prediction method to address the uncertainty. Recently, complex networks have been greatly paid attention since it can efficiently model the complexity, especially to deal with different nodes or facts interacting with each other [49], which makes complex network widely used in many applications such as identifying influential nodes [50]–[52], social dilemma [53], [54] and topology analysis of the key parameters in complex systems [55]–[57].

With the visibility graph [58], a new tool to transform time series into complex networks [55], [59]–[61], network analysis has been applied in time series analysis [62], [63]. Many studies have shown that complex networks can help predict time series, and the effective information is mined by researching the complex networks [64], [65]. Liu and Lâĺâź [66] proposed a method to measure the similarity of two nodes, some scholars use this method for time series [13], [67]–[70]. However, this method needs to

iteratively calculate the similarity of two nodes, which is very time-consuming. To address this issue, a fast method is proposed to calculate the similarity of two nodes without iteration. the proposed method is mainly divided into four steps. Firstly, the time series is converted into complex networks. Then the new method is used to calculate the similarity between the nodes. Finally the k nodes which are the most similar to the last node are determined, and the weights are calculated to make a prediction.

The structure of this article is as follows: preliminaries will be introduced in Section 2. Section 3 will introduce the proposed method. The experiments will be carried out in Section 4, and finally the summary will be given in Section 5.

II. PRELIMINARIES

In this section, some basic knowledge will be introduced including visibility graph [71], transition probability [66], and Markov chain [72].

A visibility graph [73], [74] algorithm is an algorithm that converts a time series into complex networks [58], [75]. The constructed graph inherits several properties of the series. The periodic sequence is converted into a regular graph, and the random sequence is converted into a random graph.

Definition 1: A time series is defined as $Y = \{y_1, y_2, \ldots y_N\}$, where $i \epsilon T$ and T is the index of time [76].

Definition 2: Connectivity in time series is defined as follows [58].

$$y_k < y_j + (y_i - y_j)\frac{j-k}{j-i} \quad \& \; i < k < j \tag{1}$$

If the points (i, y_i) and (j, y_j) satisfy the above formula, then the two points are connected.

Note that the visibility graph has a total of three properties.

- Connected: Each adjacent point is connected.
- Undirected: the visibility is non-directional.
- Mapping in-variance: visibility criterion is invariant for both horizontal and vertical scaling and horizontal and vertical translation.

The transition probability is the key parameter in link prediction [66].

Definition 3: The transition probability is defined by [66]

$$P_{ij} = \frac{I_{ij}}{D_i} \tag{2}$$

where P_{ij} is the probability that i turns to j, D_i is the degree of point (i, y_i), and

$$I_{ij} = \begin{cases} 1, & y_k < y_j + (y_i - y_j)\dfrac{j-k}{j-i} \quad \& \; i < k < j \\ 0, & otherwise \end{cases}$$

Definition 4: Given a sequence of random variables $\{X_1, X_2, \ldots, X_N\}$, a discrete time of Markov chain is defined as follows [72], [77].

$$P(X_{N+1}|X_N, \ldots, X_1) = P(X_{N+1}|X_N) \tag{3}$$

which means that the probability of next time $N + 1$ is only depends on the present time N and not on the previous times.

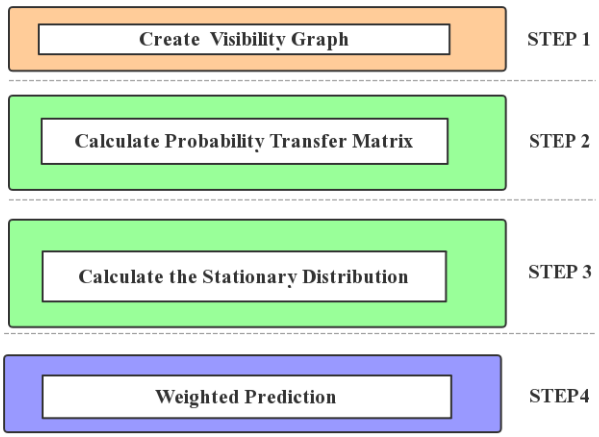

FIGURE 1. Flow chart of proposed method.

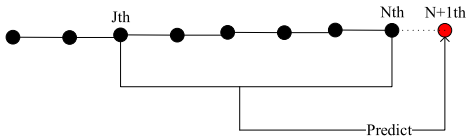

FIGURE 2. Predict time series based on complex networks.

III. PROPOSED METHOD

This paper proposes a new method that uses the past N data points to predict the $(N + 1th)$ data point.

The flow chart of the proposed method is shown in FIGURE 1.

Step 1: Convert time series $Y = \{y_1, y_2, \ldots y_N\}$ into complex networks according to *Eq.*(1). The visibility algorithm is an algorithm that converts time series into a visibility graph [58].

Step 2: Calculate the probability transfer matrix according to *Eq.*(2). The transition probability of two nodes can be regarded as a similar measure of two nodes. Zhang *et al.* [67] explained in detail why the transition probability can be used to measure the similarity of two nodes. However, the method proposed by Zhang *et al.* [67] is very time consuming. It is necessary to present a faster way.

Step 3: A method of similarity of new computational nodes is proposed based on stationary distribution of Markov chains in this step. The stationary distribution of the Markov chain is determined by the transition matrix and the initial distribution. Note that we assume that the time series $Y = \{y_1, y_2, \ldots y_N\}$ is a Markov chain.

In the method of time series prediction based on complex networks, a key step is to calculate the similarity between the *Nth* node and the previous $N - 1$ nodes. Then, the value of the $(N + 1)th$ node is determined by the *Nth* node and the *Jth* node. Where the *Jth* node is the node most similar to the *Nth* node, which can be seen in FIGURE 2.

To the best of our knowledge, most current methods of calculating similarity are based on link prediction. The advantage of this method is that it can calculate the similarity of any

two nodes in a complex network. However, isn't the similarity of such compute nodes fully applicable to time series? In fact, it is only necessary to calculate the similarity between the *Nth* node and the previous $N-1$ nodes. This method uses the value of the stationary distribution of the probability transfer matrix as the similarity, which is presented as follows.

$$V_{Nj}^{T}(j) = P^{T} V_0 \tag{4}$$

where V is the N-dimensional column vector, $V_{Nj}^{T}(j)$ is the similarity between the *Nth* node and the *Jth* node, and V_0 is the probability distribution of the initial nodes. Some methods such as distance function [78]–[80], entropy method [81], [82], bio-inspired model [83], [84] and divergence [85]–[87] are used to determine the similarity measure. In the proposed method, we set T ensuring that the $\left\| V^{T+1} - V^{T} \right\|$ are less than 10^{-5}. In the link prediction, the similarity of any two nodes is calculated as follows [67].

$$S_{ij}^{SRW} = \sum_{t=0}^{T} \frac{k_i}{2|E|} P^{t} \pi_i + \frac{k_j}{2|E|} P^{t} \pi_j \tag{5}$$

where S_{ij}^{SRW} is the similarity between node i and node j, k_i and k_i are the degrees of nodes i and node j, $|E|$ is the number of edges in the network. Note that π is different from V. π_i is an N-dimensional column vector, where the value of the *i-th* element is 1, and the value of the other elements is 0. V is a column vector of N, representing the probability distribution of all nodes, where the values of all elements are between 0 and 1.

Normally, calculating the similarity between the *Nth* node and the previous $N-1$ nodes requires $N-1$ calculations based on link prediction. However, in the proposed method, it only needs to be calculated once [67].

It is noted that one property of the Markov chain is utilized in calculating the similarity of nodes: the limit distribution is the same as the stationary distribution. The process of certification is provided in Section V.

Step 4: This step first looks for the top k maximum values in V. Here, it is considered that the top k maximum values points are most similar to the *Nth* point.The final prediction can be calculated as follows.

$$y_{N+1} = \sum_{r=1}^{k} \frac{V_r}{\sum_{j=1}^{k} V_j} \left(\frac{y_N - y_r}{N - r} ((N+1) - N) + y_N \right) \tag{6}$$

where $V_{Nj}^{T}(j)$ is recorded as V_j.

How to choose the optimal k does play a role in improving the accuracy. After our best efforts and attempts, a rule of experience is proposed.

(1) If the trend of the time series is an upward trend, usually the k value is set to 2.

(2) If the trend of the time series has periodicity, usually the k value is set to 4.

(3) If the trend of the time series is a downward trend, the k value is usually set to 2.

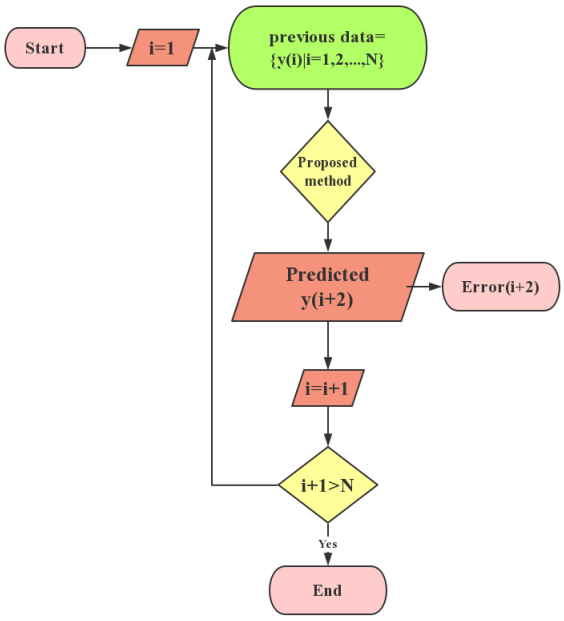

FIGURE 3. Flow chart of the prediction.

IV. APPLICATION

This section firstly verifies the effectiveness of the method through CCI data. The CCI data set is the engineering cost data [88], [89], with a total of 295 data points. From January of 1990 to July of 2014. The flow chart of the whole experiment is shown below.

In order to assess the accuracy of the forecast, a total of 5 evaluation criteria are chose including normalized root mean square error (NRMSE), mean absolute percentage error (MAPE), symmetric mean absolute percent error (SMAPE), mean absolute difference (MAD), Root Mean Squared Error (RMSE) [90].

A. STEP BY STEP PREDICTION

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} |\hat{y}_i - y_i|^2}}{\hat{y}_{max} - \hat{y}_{min}} \tag{7}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|\hat{y}_i - y_i|}{\hat{y}_i} \times 100 \tag{8}$$

$$SMAPE = \frac{2}{N} \sum_{i=1}^{N} \frac{|\hat{y}_i - y_i|}{\hat{y}_i + y_i} \tag{9}$$

$$MAD = \frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i|^2} \tag{11}$$

The flow chart of the prediction is shown in Figure 3.

TABLE 1 shows a comparison of the three methods including SMA [19], Zhang *et al.* [67] method and proposed

TABLE 1. Comparison in three methods.

	MAD	RMSE	MAPE(%)	NRMSE(%)
SMA(k=1) [19]	21.59	32.73	0.3110	0.6350
Zhang *et al.* [67]	20.05	29.33	0.2889	0.5690
Proposed method	**19.88**	**28.06**	0.2899	**0.5455**

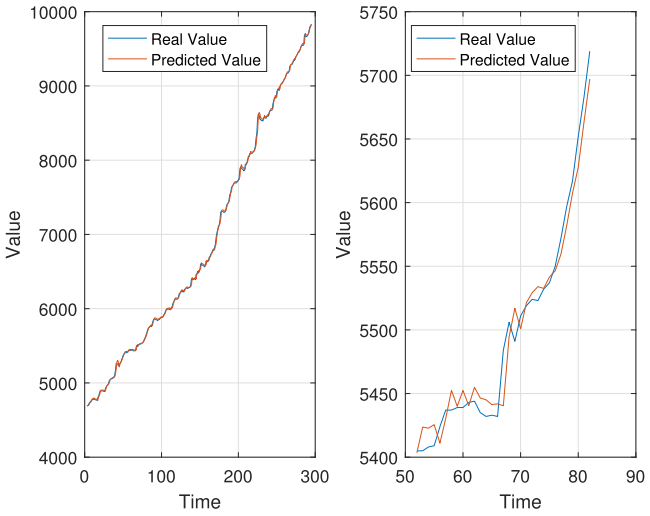

FIGURE 4. The real values and predicted values of CCI.

method. It can be seen that the proposed method performs better than the previous method on three indicators.

FIGURE 4 shows a comparison of real and predicted values in the CCI data set. It can be seen that the overall predicted value is very consistent with the real, but there is a partial error.

B. OUT-OF-SAMPLE PREDICTIONS

To further verify the effectiveness of the proposed method. The entire experimental process can be seen on Algorithm 1. The sliding window method is used to test. In the experiment, the sliding window was set to $L = 3, L = 6, L = 12$.

Algorithm 1

Require: Dataset, length of L;
Ensure: Average error;
  for $i = 1$ to $(N - L - 2)$ **do**
    $Traindataset == \{x|x(i), i = 1, \ldots, k + 1\}$;
    for j to L **do**
      $\hat{y} = Proposedmethod(Traindataset(k + j + 1))$;
    end for
    $Error$;
  end for
  $Averageerror$;

TABLE 2 shows the error of non-synchronization. It can be seen that the MAD, MAPE, SMAPE, and RMSE gradually increase with the increase of the step size, but the NRMSE decreases with the increase of the step size.

TABLE 2. Errors comparison in three step size.

L	MAD	MAPE	SMAPE	RMSE	NRMSE
3	30.8937	0.4522	0.4531	34.0824	185.618
6	42.1445	0.6222	0.6222	48.1535	73.4600
12	56.4889	0.8377	0.8414	65.6824	38.9931

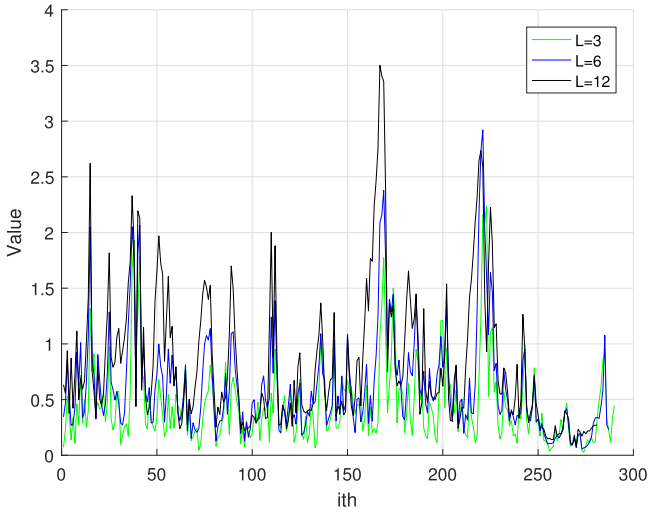

FIGURE 5. MAPE in three step size.

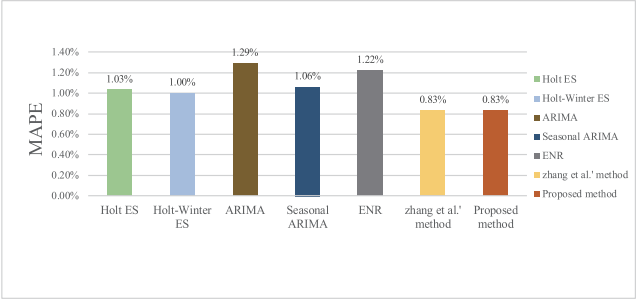

FIGURE 6. MAPE error $L = 12$ comparisons with other methods.

FIGURE 5 shows that each error of the error MAPE is in three step size.

FIGURE 6 shows the comparison of different methods on MAPE [67]. Where the time consumption is smaller, the accuracy of the proposed method is the same as that of the Zhang *et al.* [67] method.

In order to further validate the proposed method, some new data sets are utilized, Shampoo Sales Dataset, Monthly Sunspot Dataset and Daily Female Births Dataset. Shampoo Sales Dataset describes the number of Shampoo sales per month for a total of three years. Monthly Sunspot Dataset describes the monthly sunspot count for a total of 230 years. Daily Female Births Dataset describes the number of female births per day in California in 1959.

In Shampoo Sales Dataset, the data are adopted for forecast the remaining sales volume from January 5th. In the Monthly Sunspot data set, data was used from 1749 to 1956 to predict data from 1757 to 1966. In the Daily Female Births data set,

TABLE 3. Comparisons in three dataset.

Shampoo Sales	MAD	MAPE	SMAPE	RMSE	NRMSE
Zhang' method [67]	101.6157	32.743	36.0217	122.9896	21.9978
Mao's method [91]	96.9999	30.4966	31.829	118.728	21.2355
Proposed method	106.3232	34.4702	34.5245	127.6355	22.8287

Monthly Sunspot	MAD	MAPE	SMAPE	RMSE	NRMSE
Zhang' method [67]	12.2978	38.717	50.0203	16.961	10.9285
Mao's method [91]	12.107	37.3702	42.8813	16.587	10.6875
Proposed method	11.5936	33.5254	27.2917	16.0691	10.3538

Daily Female Births	MAD	MAPE	SMAPE	RMSE	NRMSE
Zhang' method [67]	7.6183	18.1347	18.3635	9.6468	19.2936
Mao's method [91]	7.5028	17.8429	17.9362	9.5013	19.0026
Proposed method	7.5581	18.1128	17.9508	9.508	19.0161

the data was predicted from January 10, 1959 to the remaining period. As can be seen in TABLE 3, the proposed method performs best in sunpot data. It surpasses other methods in five indicators. The time complexity of the proposed method is less than that of Zhang *et al.* [67] and Mao and Xiao [91].

V. CONCLUSION

Based on the stationary distribution of visibility graph and markov chains, a more efficient method is proposed to predict the time series.

The proposed method is divided into four steps. The first step is to convert the time series into a visibility graph. The second step uses the visibility graph to calculate the probability transfer matrix. The third step uses the properties of the probability transfer matrix to solve the stationary distribution. The fourth step is based on finding the point with the highest pro-k probability as the most similar point to the Nth, and the value of the $(N+1th)$ point is predicted according to the weighted coefficient.

The contribution of this paper is that a faster method to calculate similarity between Nth and previous $N-1th$ nodes is proposed. In predicting that the value of the N + 1th node is jointly determined by the first k nodes, it seems to improve the accuracy.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

APPENDIX

Definition 5: The stationary distribution $V = \{v_1, v_2, \dots v_N\}$ is defined as follows.

- $\sum_{j\epsilon E} v_j = 1$.
- $v_j = \sum_{i\epsilon E} v_i P_{ij}$.

where $PV = V$ is the matrix form of the above formula.

Definition 6: If there is a limit, for all states i and j, the limit distribution is defined as follows.

$$\lim_{n\to\infty} P_{ij}^n = \Pi_j \quad \& \sum_{j\epsilon E} \Pi_j = 1 \tag{12}$$

Theorem 1: The stationary distribution of Markov processes is equal to the limit distribution:

Proof: Assume that the limit distribution of the Markov chain $X = \{x(n), n = 1, 2, \dots\}$ is $(\Pi_1, \Pi_2, \dots)$.

$$\lim_{n\to\infty} P_{ij}^n = \Pi_j \tag{13}$$

because $p_{ij}^{n+1} = \sum_{r\epsilon E} \Pi_r \cdot P_{rj}$. So when n tends to infinity

$$\Pi_j = \sum_{r\epsilon E} \Pi_r \cdot P_{rj} \tag{14}$$

REFERENCES

[1] J. Bao, W. Chen, Y.-S. Shui, and Z.-T. Xiang, "Complexity analysis of traffic time series based on multifractality and complex network," in *Proc. IEEE 4th Int. Conf. Transp. Inf. Saf. (ICTIS)*, Aug. 2017, pp. 257–263.
[2] D. Cheng, Y. Liu, Z. Niu, and L. Zhang, "Modeling similarities among multi-dimensional financial time series," *IEEE Access*, vol. 6, pp. 43404–43413, 2018.
[3] M. Shahandashti, B. Ashuri, A. Touran, and E. Minchin, "Construction portfolio performance management using key performance indicators," *J. Adv. Perform. Inf. Value*, vol. 10, pp. 85–101, Dec. 2018.
[4] J. Wang and B. Ashuri, "Predicting ENR construction cost index using machine-learning algorithms," *Int. J. Construct. Edu. Res.*, vol. 13, no. 1, pp. 47–63, 2017.
[5] D. Zurita, M. Delgado, J. A. Carino, J. A. Ortega, and G. Clerc, "Industrial time series modelling by means of the neo-fuzzy neuron," *IEEE Access*, vol. 4, pp. 6151–6160, 2016.
[6] H. Xiong, P. Shang, J. Xia, and J. Wang, "Time irreversibility and intrinsics revealing of series with complex network approach," *Phys. A, Stat. Mech. Appl.*, vol. 499, pp. 241–249, Jun. 2018.
[7] Z. Wu, P. Shang, and H. Xiong, "An improvement of the measurement of time series irreversibility with visibility graph approach," *Phys. A, Stat. Mech. Appl.*, vol. 502, pp. 370–378, Jul. 2018.
[8] L. Rong and P. Shang, "The novel multi-scale local irreversibility analysis method based on segmentation about time series," *Nonlinear Dyn.*, vol. 95, no. 4, pp. 1–14, 2018.
[9] S. Supriya, S. Siuly, H. Wang, J. Cao, and Y. Zhang, "Weighted visibility graph with complex network features in the detection of epilepsy," *IEEE Access*, vol. 4, pp. 6554–6566, 2016.
[10] S. B. Tsai, Y. Xue, J. Zhang, Q. Chen, Y. Liu, J. Zhou, and W. Dong, "Models for forecasting growth trends in renewable energy," *Renew. Sustain. Energy Rev.*, vol. 77, pp. 1169–1178, Sep. 2016.
[11] C. Hao, W. Li, and S. Du, "Classification of eeg in eyes-open and eyes-closed state based on limited penetrable visibility graph," in *Proc. IEEE Int. Conf. Cyber Technol. Automat., Control, Intell. Syst. (CYBER)*, Jun. 2016, pp. 448–451.
[12] H. Ma, S. Leng, C. Tao, X. Ying, J. Kurths, Y.-C. Lai, and W. Lin, "Detection of time delays and directional interactions based on time series from complex dynamical systems," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 96, no. 1, 2017, Art. no. 012221.

[13] A. Ozcan and S. G. Oguducu, "Multivariate time series link prediction for evolving heterogeneous network," *Int. J. Inf. Technol. Decis. Making*, vol. 18, no. 1, pp. 241–286, 2019. doi: 10.1142/S0219622018500530.
[14] M. Zhang and D. Pi, "A new time series representation model and corresponding similarity measure for fast and accurate similarity detection," *IEEE Access*, vol. 5, pp. 24503–24519, 2017.
[15] P. Li, J. Zhang, C. Li, B. Zhou, Y. Zhang, M. Zhu, and N. Li, "Dynamic similar sub-series selection method for time series forecasting," *IEEE Access*, vol. 6, pp. 32532–32542, 2018.
[16] M. Tahmassebpour, "A new method for time-series big data effective storage," *IEEE Access*, vol. 5, pp. 10694–10699, 2017.
[17] H. Li and C. Wang, "Similarity measure based on incremental warping window for time series data mining," *IEEE Access*, vol. 7, pp. 3909–3917, 2019.
[18] G. I. Choudhary, W. Aziz, I. R. Khan, S. Rahardja, and P. Fränti, "Analysing the dynamics of interbeat interval time series using grouped horizontal visibility graph," *IEEE Access*, vol. 7, pp. 9926–9934, 2019.
[19] B. Ashuri and J. Lu, "Time series analysis of ENR construction cost index," *J. Construction Eng. Manage.*, vol. 136, no. 11, pp. 1227–1237, Nov. 2010.
[20] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.
[21] L. J. Cao and F. E. H. Tay, "Support vector machine with adaptive parameters in financial time series forecasting," *IEEE Trans. Neural Netw.*, vol. 14, no. 6, pp. 1506–1518, Nov. 2003.
[22] G. P. Zhang and M. Qi, "Neural network forecasting for seasonal and trend time series," *Eur. J. Oper. Res.*, vol. 160, no. 2, pp. 501–514, 2005.
[23] G. E. P. Box and D. A. Pierce, "Distribution of residual autocorrelations in autoregressive-integrated moving average time series models," *J. Amer. Statist. Assoc.*, vol. 65, no. 332, pp. 1509–1526, Apr. 1970.
[24] S. L. D. Ph and W. K. Li, "On fractionally integrated autoregressive moving-average time series models with conditional heteroscedasticity," *J. Amer. Stat. Assoc.*, vol. 92, no. 439, pp. 1184–1194, 1997.
[25] S. E. Said and D. A. Dickey, "Testing for unit roots in autoregressive-moving average models of unknown order," *Biometrika*, vol. 71, no. 3, pp. 599–607, 1984.
[26] V. Haggan and T. Ozaki, "Modelling nonlinear random vibrations using an amplitude-dependent autoregressive time series model," *Biometrika*, vol. 68, no. 1, pp. 189–196, 1981.
[27] A. Azadeh, M. Saberi, and S. M. Asadzadeh, "An adaptive network based fuzzy inference system–auto regression–analysis of variance algorithm for improvement of oil consumption estimation and policy making: The cases of Canada, United Kingdom, and South Korea," *Appl. Math. Model.*, vol. 35, no. 2, pp. 581–593, 2011.
[28] Q. Cai, D. Zhang, W. Zheng, and S. C. H. Leung, "A new fuzzy time series forecasting model combined with ant colony optimization and auto-regression," *Knowl.-Based Syst.*, vol. 74, pp. 61–68, Jan. 2015.
[29] S. Guan and A. Zhao, "A two-factor autoregressive moving average model based on fuzzy fluctuation logical relationships," *Symmetry*, vol. 9, no. 10, p. 207, 2018.
[30] T. Hill, M. O'Connor, and W. Remus, "Neural network models for time series forecasts," *Manage. Sci.*, vol. 42, no. 7, pp. 1082–1092, 1996.
[31] N. I. Sapankevych and R. Sankar, "Time series prediction using support vector machines: A survey," *IEEE Comput. Intell. Mag.*, vol. 4, no. 2, pp. 24–38, May 2009.
[32] F. E. Tay and L. Cao, "Application of support vector machines in financial time series forecasting," *Omega*, vol. 29, no. 4, pp. 309–317, Aug. 2001.
[33] H. Liu, I. Dzitac, and S. Guo, "Reduction of conditional factors in causal analysis," *Int. J. Comput., Commun. Control*, vol. 13, no. 3, pp. 383–390, 2018.
[34] X. Deng, W. Jiang, and Z. Wang, "Zero-sum polymatrix games with link uncertainty: A Dempster–Shafer theory solution," *Appl. Math. Comput.*, vol. 340, pp. 101–112, Jan. 2019.
[35] D. Meng, S. Yang, Y. Zhang, and S.-P. Zhu, "Structural reliability analysis and uncertainties-based collaborative design and optimization of turbine blades using surrogate model," *Fatigue Fract. Eng. Mater. Struct.*, vol. 42, pp. 1219–1227, Jun. 2018.
[36] D. Meng, M. Liu, S. Yang, H. Zhang, and R. Ding, "A fluid–structure analysis approach and its application in the uncertainty-based multidisciplinary design and optimization for blades," *Adv. Mech. Eng.*, vol. 10, no. 6, 2018, Art. no. 1687814018783410.
[37] B. Kang, P. Zhang, Z. Gao, G. Chhipi-Shrestha, K. Hewage, and R. Sadiq, "Environmental assessment under uncertainty using Dempster–Shafer theory and Z-numbers," *J. Ambient Intell. Hum. Comput.*, Feb. 2019. doi: 10.1007/s12652-019-01228-y.
[38] F. Xiao, "A novel multi-criteria decision making method for assessing health-care waste treatment technologies based on D numbers," *Eng. Appl. Artif. Intell.*, vol. 71, pp. 216–225, May 2018.
[39] Y. Han and Y. Deng, "A hybrid intelligent model for assessment of critical success factors in high-risk emergency system," *J. Ambient Intell. Humanized Comput.*, vol. 9, no. 6, pp. 1933–1953, 2018.
[40] R. Sun and Y. Deng, "A new method to identify incomplete frame of discernment in evidence theory," *IEEE Access*, vol. 7, pp. 15547–15555, 2019.
[41] R. Sun and Y. Deng, "A new method to determine generalized basic probability assignment in the open world," *IEEE Access*, vol. 7, pp. 52827–52835, 2019. doi: 10.1109/ACCESS.2019.2911626.
[42] S.-B. Tsai, "Using grey models for forecasting China's growth trends in renewable energy consumption," *Clean Technol. Environ. Policy*, vol. 18, no. 2, pp. 563–571, 2016.
[43] S.-B. Tsai, Y.-C. Lee, and J.-J. Guo, "Using modified grey forecasting models to forecast the growth trends of Green materials," *Proc. Inst. Mech. Eng. B, J. Eng. Manuf.*, vol. 228, no. 6, pp. 931–940, 2014.
[44] L. A. Zadeh, "Preliminary draft notes on a similarity-based analysis of time-series with applications to prediction, decision and diagnostics," *Int. J. Intell. Syst.*, vol. 34, no. 1, pp. 107–113, 2019.
[45] I. Dzitac, F. G. Filip, and M.-J. Manolescu, "Fuzzy logic is not fuzzy: World-renowned computer scientist lotfi a. zadeh," *Int. J. Comput. Commun. Control*, vol. 12, no. 6, pp. 748–789, 2017.
[46] F. Xiao, "A hybrid fuzzy soft sets decision making method in medical diagnosis," *IEEE Access*, vol. 6, pp. 25300–25312, 2018.
[47] R. R. Yager, N. Alajlan, and Y. Bazi, "Aspects of generalized orthopair fuzzy sets," *Int. J. Intell. Syst.*, vol. 33, no. 11, pp. 2154–2174, Nov. 2018.
[48] L. Chen and H. Yu, "Emergency alternative selection based on an E-IFWA approach," *IEEE Access*, vol. 7, pp. 44431–44440, 2019.
[49] C. Liu, C. Shen, Y. Geng, S. Li, C. Xia, Z. Tian, L. Shi, R. Wang, S. Boccaletti, and Z. Wang, "Popularity enhances the interdependent network reciprocity," *New J. Phys.*, vol. 20, no. 12, 2018, Art. no. 123012.
[50] L. Fei, Q. Zhang, and Y. Deng, "Identifying influential nodes in complex networks based on the inverse-square law," *Phys. A, Stat. Mech. Appl.*, vol. 512, pp. 1044–1059, Dec. 2018.
[51] T. Wen and W. Jiang, "Identifying influential nodes based on fuzzy local dimension in complex networks," *Chaos, Solitons Fractals*, vol. 119, pp. 332–342, Feb. 2019.
[52] M. Li, Q. Zhang, and Y. Deng, "Evidential identification of influential nodes in network of networks," *Chaos, Solitons Fractals*, vol. 117, pp. 283–296, Dec. 2018.
[53] Z. Wang, M. Jusup, L. Shi, J.-H. Lee, Y. Iwasa, and S. Boccaletti, "Exploiting a cognitive bias promotes cooperation in social dilemma experiments," *Nature Commun.*, vol. 9, Jul. 2018, Art. no. 2954.
[54] C. Shen, C. Chu, L. Shi, M. Perc, and Z. Wang, "Aspiration-based coevolution of link weight promotes cooperation in the spatial prisoner's dilemma game," *Roy. Soc. Open Sci.*, vol. 5, May 2018, Art. no. 180199.
[55] T. Wen, M. Song, and W. Jiang, "Evaluating topological vulnerability based on fuzzy fractal dimension," *Int. J. Fuzzy Syst.*, vol. 20, no. 6, pp. 1956–1967, 2018.
[56] B. Wei and Y. Deng, "A cluster-growing dimension of complex networks: From the view of node closeness centrality," *Phys. A, Stat. Mech. Appl.*, vol. 522, pp. 80–87, May 2019.
[57] T. Wen and W. Jiang, "An information dimension of weighted complex networks," *Phys. A, Stat. Mech. Appl.*, vol. 501, pp. 388–399, Jul. 2018.
[58] L. Lacasa, B. Luque, F. J. Ballesteros, J. Luque, and J. C. Nuño, "From time series to complex networks: The visibility graph," *Proc. Nat. Acad. Sci. USA*, vol. 105, no. 13, pp. 4972–4975, 2008.
[59] Z. K. Gao, M. Small, and J. Kurths, "Complex network analysis of time series," *Europhys. Lett.*, vol. 116, no. 5, Jan. 2017, Art. no. 50001.
[60] Z.-K. Gao, S. Li, W.-D. Dang, Y.-X. Yang, Y. Do, and C. Grebogi, "Wavelet multiresolution complex network for analyzing multivariate nonlinear time series," *Int. J. Bifurcation Chaos*, vol. 27, no. 8, Jul. 2017, Art. no. 1750123.
[61] P. Xu, R. Zhang, and Y. Deng, "A novel visibility graph transformation of time series into weighted networks," *Chaos, Solitons Fractals*, vol. 117, pp. 201–208, Dec. 2018.
[62] J. Zhao and Y. Deng, "Performer selection in human reliability analysis: D numbers approach," *Int. J. Comput. Commun. Control*, vol. 14, no. 3, pp. 437–452, 2019.
[63] M. Wang, A. L. M. Vilela, L. Tian, H. Xu, and R. Du, "A new time series prediction method based on complex network theory," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Dec. 2017, pp. 4170–4175.

[64] Z. Wang, M. Jusup, L. Shi, J.-H. Lee, Y. Iwasa, and S. Boccaletti, "Exploiting a cognitive bias promotes cooperation in social dilemma experiments," *Nature Commun.*, vol. 9, no. 1, p. 2954, 2018.
[65] Y. Wang, S. Wang, and Y. Deng, "A modified efficiency centrality to identify influential nodes in weighted networks," *Pramana*, vol. 92, no. 4, p. 68, 2019.
[66] W. Liu and L. Lü, "Link prediction based on local random walk," *Europhys. Lett.*, vol. 89, no. 5, 2010, Art. no. 58007.
[67] R. Zhang, B. Ashuri, and Y. Deng, "A novel method for forecasting time series based on fuzzy logic and visibility graph," *Adv. Data Anal. Classification*, vol. 11, no. 4, pp. 759–783, Dec. 2017. doi: 10.1007/s11634-017-0300-3.
[68] S. Basu and U. Maulik, "Link prediction in complex dynamic networks using multiple interdependent time series," in *Proc. IEEE Int. Conf. Comput., Power Commun. Technol. (GUCON)*, Sep. 2018, pp. 1136–1141.
[69] A. Özcan and Ş. G. Ögüdücü, "Temporal link prediction using time series of quasi-local node similarity measures," in *Proc. 15th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2016, pp. 381–386.
[70] A. Özcan and S. G. Oguducu, "Link prediction in evolving heterogeneous networks using the NARX neural networks," *Knowl. Inf. Syst.*, vol. 55, no. 2, pp. 333–360, May 2018.
[71] B. Luque, L. Lacasa, F. Ballesteros, and J. Luque, "Horizontal visibility graphs: Exact results for random time series," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 80, no. 4, 2009, Art. no. 046103.
[72] G. A. Timofeeva and N. A. Timofeev, "Forecasting credit portfolio components with a Markov chain model," *Autom. Remote Control*, vol. 73, no. 4, pp. 637–651, Apr. 2012.
[73] J. Iacovacci and L. Lacasa, "Visibility graphs for image processing," *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published.
[74] L. Lacasa and W. Just, "Visibility graphs and symbolic dynamics," *Phys. D, Nonlinear Phenomena*, vols. 374–375, pp. 35–44, Jul. 2018.
[75] Z.-K. Gao, Q. Cai, Y.-X. Yang, and W.-D. Dang, "Time-dependent limited penetrable visibility graph analysis of nonstationary time series," *Phys. A, Stat. Mech. Appl.*, vol. 476, pp. 43–48, Jun. 2017.
[76] G. E. P. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*, 3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 1994.
[77] Z. He and W. Jiang, "An evidential Markov decision making model," *Inf. Sci.*, vol. 467, pp. 357–372, Oct. 2018.
[78] C. Lu, S. Wang, and X. Wang, "A multi-source information fusion fault diagnosis for aviation hydraulic pump based on the new evidence similarity distance," *Aerosp. Sci. Technol.*, vol. 71, pp. 392–401, Dec. 2017.
[79] W. Bi, A. Zhang, and Y. Yuan, "Combination method of conflict evidences based on evidence similarity," *J. Syst. Eng. Electron.*, vol. 28, no. 3, pp. 503–513, 2017.
[80] Y. Dong, J. Zhang, Z. Li, Y. Hu, and Y. Deng, "Combination of evidential sensor reports with distance function and belief entropy in fault diagnosis," *Int. J. Comput. Commun. Control*, vol. 14, no. 3, pp. 329–343, 2019.
[81] H. Cui, Q. Liu, J. Zhang, and B. Kang, "An improved Deng entropy and its application in pattern recognition," *IEEE Access*, vol. 7, pp. 18284–18292, 2019.
[82] L. Yin and Y. Deng, "Toward uncertainty of weighted networks: An entropy-based model," *Phys. A, Stat. Mech. Appl.*, vol. 508, pp. 176–186, Oct. 2018.
[83] H. Yang, Y. Liu, Q. Wan, and Y. Deng, "A bio-inspired optimal network division method," *Phys. A, Stat. Mech. Appl.*, vol. 527, Aug. 2019, Art. no. 121259.
[84] H. Yang, Y. Deng, and J. Jones, "Network division method based on cellular growth and physarum-inspired network adaptation," *Int. J. Unconventional Comput.*, vol. 13, no. 6, pp. 477–491, 2018.
[85] L. Fei and Y. Deng, "A new divergence measure for basic probability assignment and its applications in extremely uncertain environments," *Int. J. Intell. Syst.*, vol. 34, no. 4, pp. 584–600, 2018.
[86] F. Xiao and W. Ding, "Divergence measure of Pythagorean fuzzy sets and its application in medical diagnosis," *Appl. Soft Comput.*, vol. 79, pp. 254–267, Jun. 2019.
[87] Y. Song and Y. Deng, "A new method to measure the divergence in evidential sensor data fusion," *Int. J. Distrib. Sensor Netw.*, vol. 15, no. 4, 2019, Art. no. 1550147719841295.
[88] S. M. Shahandashti and B. Ashuri, "Forecasting engineering news-record construction cost index using multivariate time series models," *J. Construction Eng. Manage.*, vol. 139, pp. 1237–1243, Sep. 2013.
[89] B. Ashuri, S. M. Shahandashti, and J. Lu, "Empirical tests for identifying leading indicators of ENR construction cost index," *Construction Manage. Econ.*, vol. 30, no. 11, pp. 917–927, 2012.
[90] C. W. J. Granger, "Some properties of time series data and their use in econometric model specification," *J. Econ.*, vol. 16, no. 1, pp. 121–130, 1981.
[91] S. Mao and F. Xiao, "Time series forecasting based on complex network analysis," *IEEE Access*, vol. 7, pp. 40220–40229, 2019.

FAN LIU was a Research Assistant with the Institute of Fundamental and Frontier Science, University of Electronic Science and Technology of China, in 2017. He worked with Prof. Deng here in Evidence Theory. He is currently a Junior Student with the Yingcai Honors College of Mathematics and Physics Basic Science (Academic Talent Program), University of Electronic Science and Technology of China. His research direction is in evidence theory, including machine learning, quantum computing, and uncertainty analysis. He received a National Scholarship and Outstanding Student Scholarship, in 2018.

YONG DENG received the Ph.D. degree in precise instrumentation from Shanghai Jiao Tong University, Shanghai, China, in 2003, where he was an Associate Professor with the Department of Instrument Science and Technology, from 2005 to 2011. In 2010, he was a Professor with the School of Computer and Information Science, Southwest University, Chongqing, China. In 2012, he was a Visiting Professor with Vanderbilt University, Nashville, TN, USA. In 2016, he was also a Professor with the School of Electronic and Information Engineering, Xi'an Jiaotong University, Xian, China. Since 2017, he has been a Full Professor with the Institute of Fundamental and Frontier Science, University of Electronic Science and Technology of China, Chengdu, China. He has published more than 100 papers in refereed journals, such as *Decision Support Systems*, *European Journal of Operational Research*, and *Scientific Reports*. His research interests include evidence theory, decision making, information fusion, and complex system modeling. He severed as the program member of many conferences, such as International Conference on Belief Functions. He severed as a Reviewer for more than 30 journals, such as the IEEE TRANSACTIONS ON FUZZY SYSTEMS. He has received numerous honors and awards, including the Elsevier Highly Cited Scientist, China, in 2014, 2015, and 2016, respectively. He severed as many editorial board members, such as an Academic Editor for the *PLOS ONE*.