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Time Series Forecasting Based on Complex Network Analysis

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ABSTRACT Time series forecasting, especially from the perspective of the network, has been a hot research topic. In this paper, based on the analysis of complex network, a novel method is proposed for more accurate time series predictions. First, time series data are mapped into a network by visibility graph. Then, the link prediction method is adopted to calculate the similarity index. Considering that node distance is an important factor in the network, we take that into account to determine the weight coefficients and improve the predictive results. To fully verify the validity of the proposed method, it is applied to some representative time series data sets with different characteristics. The data values are recorded daily, monthly, and yearly. The error measurement and correlation analysis show that our method has a good prediction performance. It is believed that this paper will not only contribute to time series forecasting in theory but also take effect in practice.

INDEX TERMS Complex network, link prediction, node distance, time series, visibility graph.

I. INTRODUCTION

Time series is a data sequence in chronological order [1]. There are many typical examples of time series, like solar irradiance [2], probabilistic prediction [3] and so forth [4], [5]. Time series research includes many aspects, such as time series analysis [6], data aggregation and storage [7], [8], time series prediction [9], [10]. Time series forecasting is to predict future data or variation tendency by analyzing historical data and it is a hot research topic because of its wide applications in finance [11], construction costs prediction [12], and some other fields.

To make accurate predictions, many forecasting methods have been proposed [13]. Simple moving average (SMA) [14] and exponential smoothing (ES) [15] are two simple forecasting methods. Besides, autoregressive integrated and moving average (ARIMA) [16] and seasonal ARIMA models are developed that can study linear and stationary time series. Commonly, uncertainties and fluctuations may bring some forecasting errors [17]–[19]. Researchers have conducted many studies on uncertainties [20], [21]. Due to the efficiency to handle uncertainty [22], [23], fuzzy sets theory has been investigated a lot and it also can be used in time series prediction [24], [25]. Apart from that, some new methods have been proposed by many other researchers and scientists to achieve better predictability [26].

These theories and models are considerably valuable. However, they still have their limitations. Although SMA model can predict future values directly and it is easy to implement, it is less accurate. ARIMA model can improve the accuracy but it needs many observed values to train parameters when modelling. Besides, it is only useful for some specific forecast targets so it can not be applicable to predict different kinds of time series. Therefore, it is urgent to find new methods that can improve prediction accuracy and are easy to implement. Since these existing direct prediction methods have different shortcomings, we can consider the problem of time series prediction from other perspectives. Complex network has been a popular academic research direction for its widespread applications [27]–[29]. One possible solution is to use the network approach as complex network has a close relationship with the time series [30], [31], and the network can be used to identify time series information [32], [33]. In some ways, complex network can also make predictions through reasonable analysis [34]. The real systems are very complicated with many factors interacting

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with each other [35]–[37]. As a result, complex network analysis is widely used due to its efficiency to model the relationship between each factor or node [38]. It is promising to analyze time series in network models.

Recently, a novel perspective that complex network can be used to study time series has attracted much attention. The visibility graph, proposed by Lacasa *et al.* [39] is considered to be a bridge between time series and complex network. A time series can be mapped into a graph by visibility algorithm. The properties of time series are also inherited in the graph. Based on visibility graph, many researchers have studied time series through network. Jiang *et al.* used visibility graph to aggregate time series data and successfully applied it to water management [40]. Lacasa *et al.* [41] studied visibility graph to research Fractional Brownian Motion (FBM) which could be used to study a real time series appearing in diverse scientific fields. Taking advantages of visibility graph theories, Donner and Donge found out the potentials and possible pitfalls by geophysical time series [42]. Inspired by these researches, we can use the visibility algorithm to convert the time series into a network. Then time series can be studied in the network using visibility graph.

Besides, the missing link forecasting is supposed to be accounted urgently [43], [44]. It should be pointed out that modeling uncertainty of link in complex network has been paid great attention based on belief function [45]–[47] and entropy function [48], [49]. In order to solve this problem, Liu and Lü introduced a link prediction method based on local random walk (*LRW*) [50]. Considering the relationship between nodes and links in the network [51], [52], link prediction is an efficient way to explore whether there exists a link between two nodes.

In this paper, we propose a novel method for time series forecasting based on complex network analysis. Specifically, a time series is first transformed into a network by visibility graph. Then link prediction method is adopted to calculate the similarity between two nodes. Considering that node distance is a vital element in the network, we take it into account to determine the weight coefficients and obtain the prediction results. To demonstrate the validity of proposed method, different kinds of time series datasets, including Taiwan Capitalization Weighted Stock Index (TAIEX), State Bank of India Share (SBI) share price at BSE, Construction cost index (CCI), and university enrollment are adopted in the experimental section. The comparison results and error analysis show that our method has a good prediction performance.

The structure of this paper as follows: Section 2 introduces some basic concepts. In Section 3, the proposed method is illustrated in detail. Section 4 demonstrates the predictability of the method by some different experiments. Section 5 summarizes the paper and gives a brief conclusion.

II. PRELIMINARIES

In this section, we will give a brief introduction to some of the basic theories involved in the proposed method.

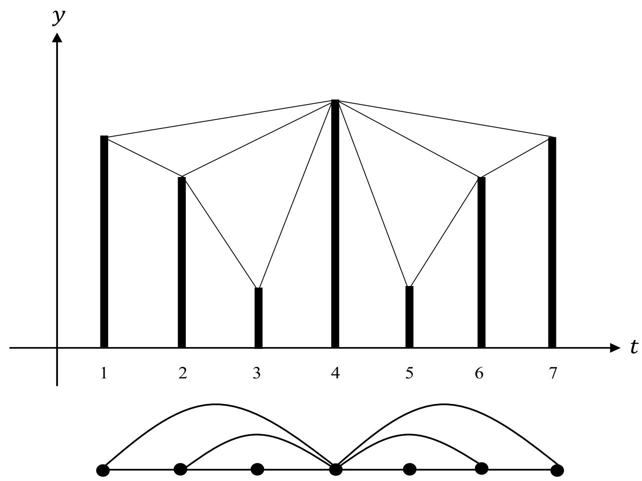

FIGURE 1. The description of visibility graph: A time series including 7 data values is converted to a visibility graph. The vertical bars represent nodes and the edges connecting two bars represent links in the network.

A. VISIBILITY GRAPH

Lacasa *et al.* [39] first proposed visibility graph to characterize time series from the perspective of complex network. The visibility algorithm, which can transform a time series into a network, is defined as follows.

Two time series data (t_1, y_1) and (t_2, y_2) are considered as two visible and connected nodes in a network, if any data value (t_3, y_3) between them fulfills (1).

$$y_3 < \frac{t_2 - t_3}{t_2 - t_1}(y_1 - y_2) + y_2. \tag{1}$$

As presented in Fig. 1, a vertical bar represents a node and the edge connecting two vertical bars represents a link in the network. Two nodes can be connected if they meet the requirement of visibility criteria.

B. LINK PREDICTION

Link prediction is able to explore potential links in the network. It is believed that two nodes tend to be linked if the have higher similarity index. Based on *LRW*, Liu and Lü proposed an efficient method to predict missing links by defining the node similarity [50].

In a network, the probability that a random walker departing from node x is denoted by $\vec{\pi}_x$. In t steps (t is a large enough value to ensure the walker can fully walk in the network), $\vec{\pi}_x(t)$ meets the following requirement:

$$\vec{\pi}_x(t) = P^T \vec{\pi}_x(t-1). \tag{2}$$

It should pointed out that P^T is the transpose of transition probability matrix P. The probability of moving from node x to node y in one step is denoted by $\vec{\pi}_{xy}$. $P_{xy} = \frac{a_{xy}}{k_x}$, where $a_{xy} = 1$ if point x is linked to point y, otherwise $a_{xy} = 0$. Besides, k_x means the degree of point x. $\vec{\pi}_x(0)$ is an $N \times 1$ vector indicating the initial state of node x, where the x-th element is equal to 1 and the others are 0.

Equation (3) presents the definition of the similarity between node x and node y [50].

$$S_{xy}^{LRW}(t) = \frac{k_x}{2|E|}\pi_{xy}(t) + \frac{k_y}{2|E|}\pi_{yx}(t), \tag{3}$$

where $|E|$ is the total number of edges in the network. Finally, according to [50], the higher similarity between node x and node y can be obtained by adding up the results of S_{xy}^{LRW} in each step. The result is calculated by (4) after a superposed random walk (SRW).

$$S_{xy}^{SRW}(t) = \sum_{l=1}^{t} S_{xy}^{LRW}(l). \tag{4}$$

C. NODE DISTANCE

According to [34], the node distance in a visibility graph is defined by (5).

$$d_{i\to j} = \left|t_i - t_j\right|, \tag{5}$$

where t_i and t_j are the corresponding time values in point (t_i, y_i) and node (t_j, y_j), respectively.

III. THE PROPOSED METHOD

In this section, the time series prediction method including five main steps is proposed.

Step 1 (Transform a Time Series to a Visibility Graph): A given time series $T = \{(t_1, y_1), (t_2, y_2), ..., (t_N, y_N)\}$ can be transformed into a visibility graph by (1) and the corresponding figure is shown in the lower part of Fig. 1.

Step 2 (Calculate Node Similarity): The similarity of any two nodes is firstly calculated by (3). Then, to sum the results of S_{xy}^{LRW}, a higher similarity is obtained based on (4).

Step 3 (Find Out the Most Similar Node): The similarities between the last node N and the preceding $(N-1)$ nodes are represented by $S^{SRW} = \left[S_{1N}, S_{2N}, \ldots, S_{MN}, \ldots, S_{(N-1)N}\right]$. The maximum value of S^{SRW} is denoted as S_{MN}. Accordingly, node (t_M, y_M) corresponding to S_{MN} is identified as the most similar point to node (t_N, y_N).

Step 4(Determine Node Distance): Based on (5), the distance between two most similar points (t_M, y_M) and (t_N, y_N), is calculated by (6).

$$d_{M\to N} = |t_N - t_M|, \tag{6}$$

If the node to be predicted is denoted as (t_{N+1}, y_{N+1}), the distance between the last node (t_N, y_N) and its next point (t_{N+1}, y_{N+1}) is calculated by (7). Similarly, the distance between node (t_M, y_M) and future node (t_{N+1}, y_{N+1}) is determined by (8).

$$d_{N\to N+1} = |t_{N+1} - t_N|. \tag{7}$$

$$d_{M\to N+1} = |t_{N+1} - t_M|. \tag{8}$$

For example, in Fig. 2, the distance between node (t_4, y_4) and node (t_7, y_7), i.e. d_{47}, is equal to 3.

Step 5 (Make Predictions): Based on the consideration of node similarity and node distance, the prediction method is determined.

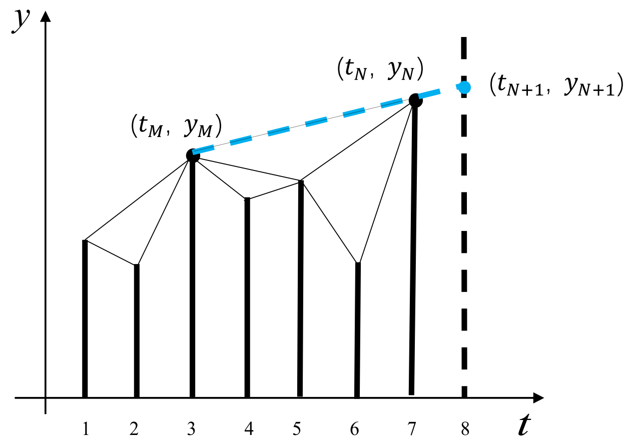

FIGURE 2. The two most similar points, node (t_3, y_3) and node (t_7, y_7) are directly connected to determine the value of y_8.

Firstly, it is in consideration of the two following significant factors that we combine node (t_M, y_M) and node (t_N, y_N) to determine the future node (t_{N+1}, y_{N+1}).

1) The most similar node (t_M, y_M)
   Time series forecasting predicts future values based on previously observed values. The node (t_M, y_M) is the representative of the previous data. It is considered to carry all the historical information so it can be used to predict the future value.
2) The last observed node (t_N, y_N)
   The node (t_N, y_N) is the closest point to the future node (t_{N+1}, y_{N+1}). Besides, it will be directly connected to node (t_{N+1}, y_{N+1}). Therefore, the last observed value y_N is supposed to have an direct impact on the predicted value y_{N+1}.

As node (t_M, y_M) and node (t_N, y_N) has the highest similarity, they are linearly connected to calculate the future value of y_{N+1}.

$$y_{N+1} = y_N + \frac{y_N - y_M}{t_N - t_M}(t_{N+1} - t_N). \tag{9}$$

As shown in Fig. 2, node (t_3, y_3) and node (t_7, y_7) are directly linked to determine the node (t_{N+1}, y_{N+1}), i.e. (t_8, y_8).

Furthermore, to improve the forecasting results, the node distance obtained from *Step* 4 is taken into account to determine the weight coefficients of y_{N+1} and y_N, respectively.

Commonly, the further the node (t_M, y_M) is from the point (t_N, y_N), the more important the node (t_M, y_M) is as it carries more historical information. Conversely, if node (t_M, y_M) is pretty close to node (t_N, y_N), the importance of node (t_M, y_M) is weakened because it contains less information about the past and then takes almost the same effect as node (t_N, y_N) for future predictions.

As shown in Fig. 3, node (t_M, y_M) and node (t_N, y_N) becomes closer from t_{M1} to t_{M3} and the distance $d_{M\to N}$ is getting smaller at the same time.

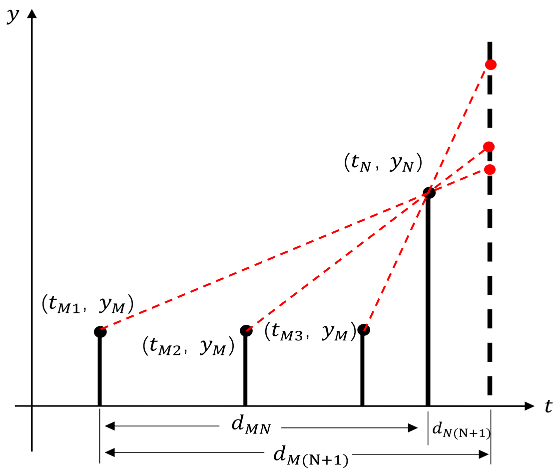

FIGURE 3. As node (t_M, y_M) moves from t_{M1} to t_{M3}, the distance d_{MN} is getting smaller. The historical information that node (t_M, y_M) carries is less and its importance is weakened meanwhile.

On the basis of such consideration, the weight coefficients are defined by (10) and (11).

$$w_{N+1} = \frac{d_{M \to N}}{d_{M \to N+1}}, \tag{10}$$

$$w_N = \frac{d_{N \to N+1}}{d_{M \to N+1}}, \tag{11}$$

where w_{N+1} denotes the weight coefficient of y_{N+1} and w_N denotes the weight coefficient of the last observed value y_N. Fig. 4 describes it in a more vivid way.

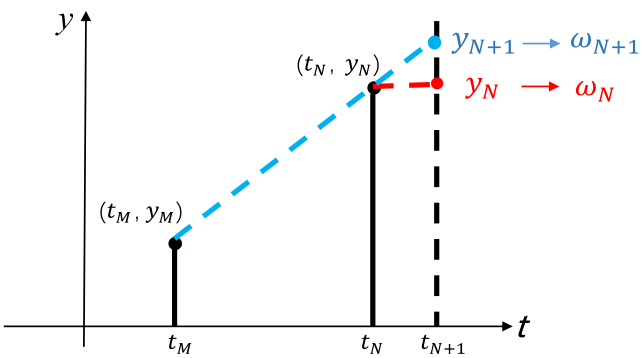

FIGURE 4. w_{N+1} (blue curve) is the weight coefficient of y_{N+1} and w_N (red curve) is the weight coefficient of y_N.

As can be seen from (10) and (11), if $d_{M \to N}$ increases, the weight coefficient of y_{N+1}, i.e. w_{N+1}, becomes larger while w_N gets smaller. Conversely, w_{N+1} will be smaller and w_N gets larger when $d_{M \to N}$ decreases. Therefore, the final prediction results are calculated by (12).

$$\hat{y}_{N+1} = w_{N+1} \times y_{N+1} + w_N \times y_N. \tag{12}$$

The proposed method is summarized by Algorithm 1 and Fig. 5 shows the process in a more vivid way.

Algorithm 1 The Process of the Proposed Method

Input: Time series dataset T: N data values

Output: The prediction value of $\hat{y}_{N+1}$

function TIME SERIES PREDICTION
- Transform time series T into a graph
- Calculate node similarity S_{xy}^{SRW}
- Find two most similar points (t_M, y_M) and (t_N, y_N)
- Determine node distance $d_{M \to N}$
- $y_{N+1} \leftarrow y_N + \frac{y_N - y_M}{t_N - t_M}(t_{N+1} - t_N)$
- $\hat{y}_{N+1} \leftarrow w_{N+1} \times y_{N+1} + w_N \times y_N$
- **return** $(t_{N+1}, \hat{y}_{N+1})$

end function

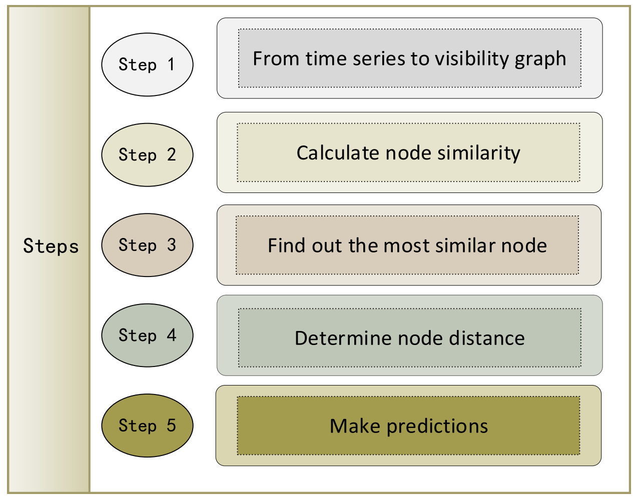

FIGURE 5. The flowchart of the proposed method.

IV. EXPERIMENTS AND ANALYSIS

In this section, the proposed method is applied to some representative datasets in different fields. These data values with different characteristics are published daily, monthly, and yearly, respectively.

In order to evaluate the experimental results, we use four error indicators, i.e. mean absolute difference *(MAD)*, mean absolute percentage error *(MAPE)*, root mean square error *(RMSE)*, and normalized root mean squared error *(NRMSE)*. They are defined by (13)-(16).

$$MAD = \frac{1}{N}\sum_{t=1}^{N}\left|\hat{y}(t) - y(t)\right| \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|\hat{y}(t) - y(t)\right|}{y(t)} \tag{14}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}[\hat{y}(t) - y(t)]^2} \tag{15}$$

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{t=1}^{N}[\hat{y}(t) - y(t)]^2}}{y_{max} - y_{min}} \tag{16}$$

TABLE 1. **The errors results of *RMSE* for TAIEX forecasting.**

Prediction methods	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average
Chen *et al.* [53]	80	60	110	112	79	54	148	167	149	107
Yu *et al.* [54]	61	67	105	135	70	54	133	151	142	102
Propsed method	46	42	72	94	58	52	133	119	108	80

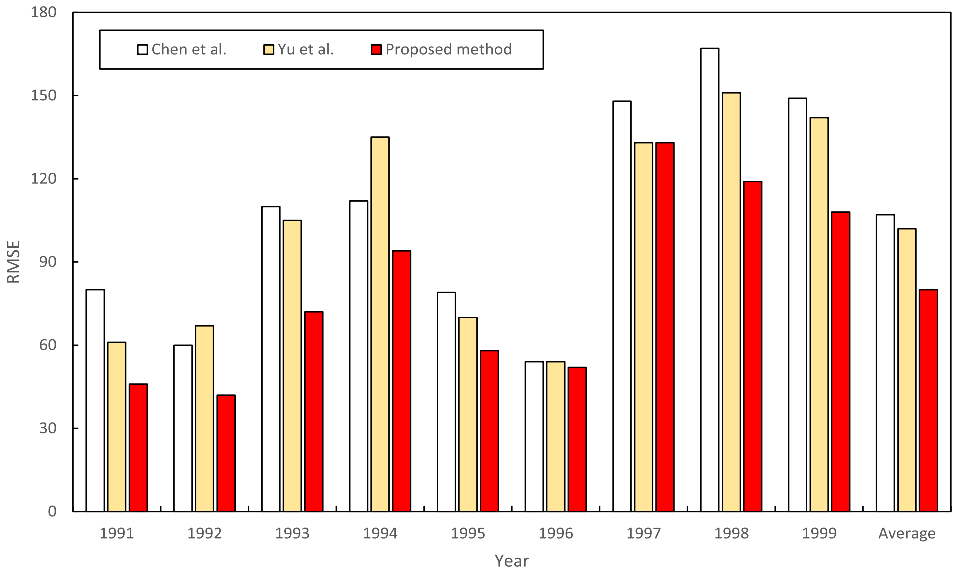

FIGURE 6. **Comparison of *RMSE* for TAIEX forecasting.**

TABLE 2. **The comparison of error measurement and correlation analysis in SBI prediction.**

Prediction methods	RMSE	MAPE(%)	R	R^2
Pathak and Singh [55]	205.96	8.95	0.8686	0.7544
Joshi and Kumar [56]	200.17	9.52	0.8821	0.7781
Bisht *et al.* [57]	327.22	1.49	0.9821	0.9645
Proposed method	199.03	7.97	0.9056	0.8201

where $\hat{y}(t)$ is the predicted value, $y(t)$ is the true value and N is the total number of $\hat{y}(t)$.

A. FINANCIAL TIME SERIES FORECASTING

In order to evaluate the predictive performance of the proposed method in financial field, we use it to predict TAIEX and SBI share price at BSE.

1) TAIEX FORECASTING

Taiwan Capitalization Weighted Stock Index (TAIEX) is a stock market index that releases every day. As one of the main indicators of Taiwan's economic trend, it fluctuates greatly and attracts many investors and economists [53], [54].

In this case, the index values from 1991 to 1999 are selected as the whole data sets. Considering the data go through a long span time, they are divided into 9 groups by year. In each group, the index values of the first ten months are applied to

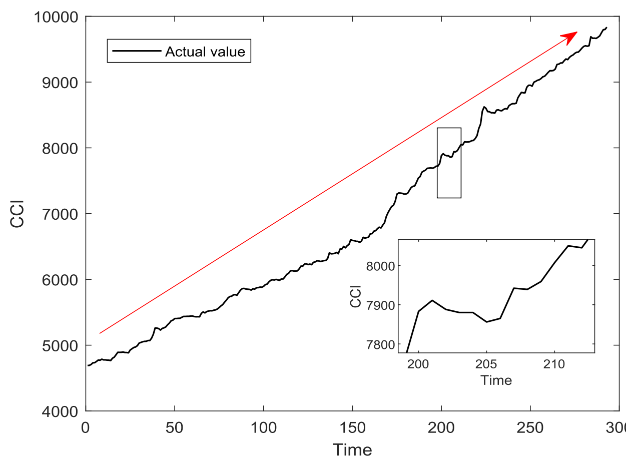

FIGURE 7. **A CCI data set from January 1990 to July 2014. It increases during a long period but fluctuates in a short time.**

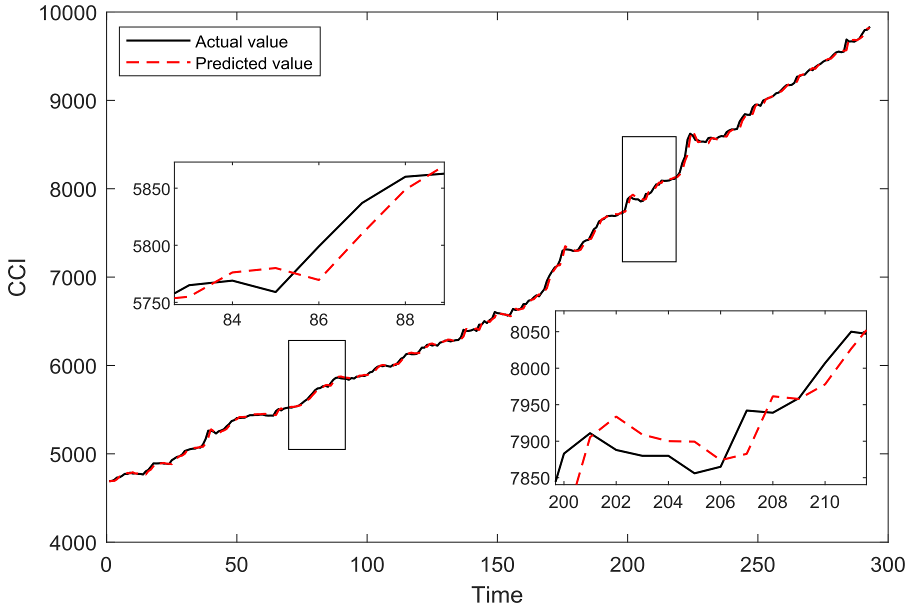

FIGURE 8. The actual values (black curve) and predicted values (red curve) of CCI.

TABLE 3. The comparison for CCI forecasting of the three methods.

Prediction methods	MAD	RMSE	MAPE(%)	NRMSE(%)	R	R^2
SMA(k=1)	21.59	32.73	0.3110	0.6350	0.9998	0.9997
Zhang *et al.* [34]	20.05	29.33	0.2889	0.5690	0.9998	0.9997
Proposed method	19.30	28.16	0.2797	0.5462	0.9998	0.9997

predict the last two months. The errors results of *RMSE* for three different forecasting methods are listed in Table 1 and plotted in Fig. 6. As can be seen, the proposed method has the minimum error compared to other models.

2) SBI SHARE PRICE FORECASTING

The SBI share prices fluctuate greatly, so they are ideal for testing the predictability of the method. The time series data values from April 2008 to March 2010 are chosen as a universe dataset. The data from April 2008 to February 2010 are adopted to predict the data values from August 2008 to March 2010. Table 2 lists the error measurement and correlation analysis of some classic and recent methods.

As can be seen, the proposed method has minimum the *RMSE* compared with other methods. In addition, correlation coefficient ($R > 0.9$) indicates that the predicted and true values are highly correlated.

B. CCI FORECASTING

Construction Cost Index (CCI) published by Engineering News Record (ENR) monthly. Many civil engineers and cost analysts have studied on CCI since it contains vital price information about building industry [58], [59].

A CCI data set from January 1990 to July 2014 (295 data values), is adopted as the universe set in this study. As shown in Fig. 7, it increases during a long period while fluctuates a lot in a short time. To show the predictability of the proposed method, all the 295 data values are adopted. Specifically, the data values from January 1990 to June 2014 are used to predict data from March 1991 to July 2014.

Fig. 8 presents the actual values (black curve) and predicted values (red curve) of CCI. As can be seen, the red curve is very close to the black one, which roughly indicates that the proposed method has a good predictive performance. However, there still exists continuous fluctuations that may cause forecasting errors (As shown in rectangular boxes in Fig. 8).

To better illustrate the prediction performance of the method, it is compared with classical time series prediction method and network approach, including Simple Moving Average (SMA) model [60] and Zhang *et al.* [34] method. Table 3 lists the forecasting errors of the three methods in detail and Fig. 9 compares the errors in a more vivid way.

The results show that the proposed method can improve the accuracy compared with both classic and recent network methods. Although the improvement is not so big, it is still

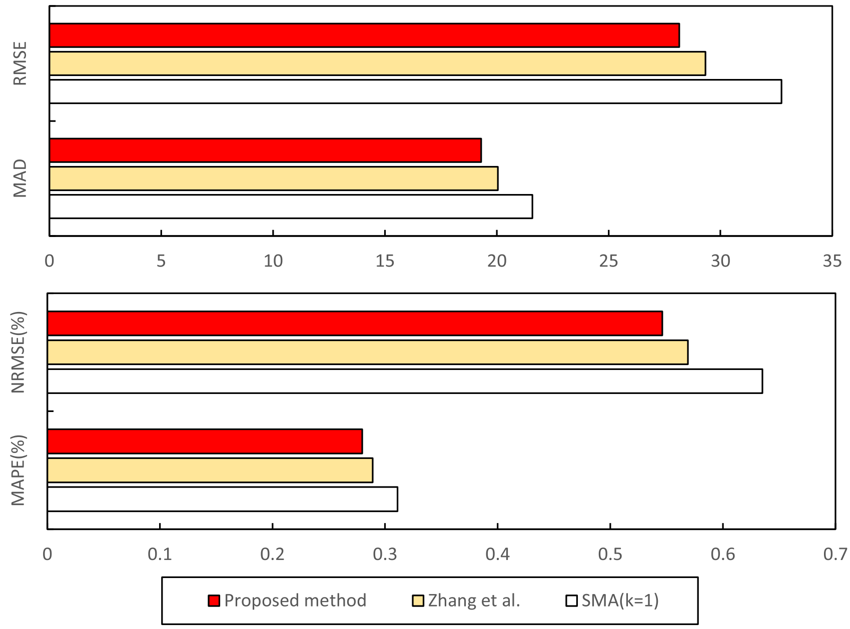

FIGURE 9. The comparison of CCI forecasting errors by the measurement of four indicators.

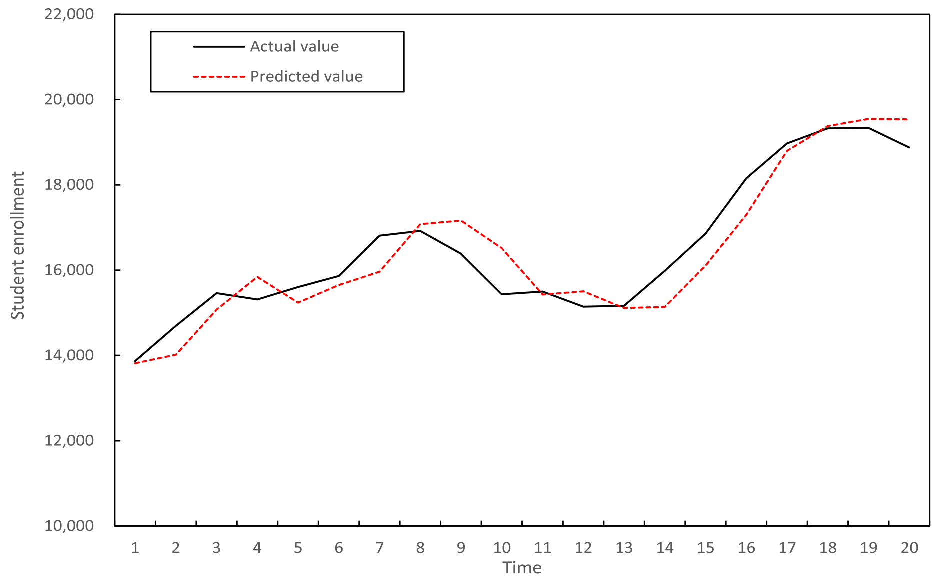

FIGURE 10. The actual values (black curve) and predicted values (red curve) of student enrollment.

considerably important for cost analysts to make budgets. In the engineering field, even 0.1% improvement can create huge benefits, especially when it comes to millions or billions of construction projects.

C. UNIVERSITY ENROLLMENT FORECASTING

In this experiment, the proposed method is used to predict the enrollment of the University of Alabama.

The enrollment data from 1971 to 1992 is chosen as a universal data set. Likewise, the first two data values are adopted to predict the enrollment of 1973. Then the predicted enrollments from 1973 to 1992 can be obtained after this step is iterated for 20 times.

The actual enrollment of the University of Alabama and predicted results from five different models are presented in Table 4. The experimental errors and statistic performance of the methods are listed in Table 5. It is obvious that our method has improved the forecasting accuracy compared with the first three methods, but less accurate than Kumar and Gangwar's method. Besides, the correlation coefficients of the proposed method indicate that there is a good correlation between observed and predicted values. From Fig. 10,

TABLE 4. The forecasting results of student enrollment.

Year	Actual	Chou [61]	Pathak and Singh [55]	Gangwar and Kumar [62]	Kumar and Gangwar [63]	Proposed
1971	13055					
1972	13563	14025	13250	14586	13693	
1973	13867	14568	13750	14586	13693	13817.0
1974	14696	14568	13750	15363	14867	14019.0
1975	15460	15654	14500	15363	15287	15073.7
1976	15311	15654	15375	15442	15376	15842.0
1977	15603	15654	15375	15442	15376	15236.5
1978	15861	15654	15625	15442	15376	15650.7
1979	16807	16197	15875	15442	16523	15961.3
1980	16919	17283	16833	17064	16606	17076.4
1981	16388	17283	16833	17064	17519	17162.2
1982	15433	16197	16500	15438	16606	16520.6
1983	15497	15654	15500	15442	15376	15429.6
1984	15145	15654	15500	15442	15376	15501.1
1985	15163	15654	15125	15363	15287	15113.5
1986	15984	15654	15125	15363	15287	15136.0
1987	16859	15654	16833	15438	16523	16105.8
1988	18150	16197	16667	17064	17519	17296.5
1989	18970	17283	18125	19356	19500	18795.5
1990	19328	18369	18750	19356	19000	19380.0
1991	19337	19454	19500	19356	19500	19547.0
1992	18876	19454	19500	19356	19500	19538.5

TABLE 5. The forecasting error measurement and statistical performance analysis of the five methods.

Prediction methods	MAD	RMSE	MAPE(%)	NRMSE(%)	R	R^2
Chou [61]	605.00	781.47	3.6075	12.4399	0.8866	0.7860
Pathak and Singh [55]	493.71	646.67	2.9883	10.2940	0.9373	0.8785
Gangwar and Kumar [62]	476.24	642.68	2.9672	10.2305	0.9243	0.8544
Kumar and Gangwar [63]	386.24	493.56	2.3366	7.8568	0.9594	0.9205
Proposed method	455.64	559.36	2.7858	8.8984	0.9426	0.8886

we can see that the actual and the predicted enrollments by the proposed method undergo the almost same variation tendency.

D. ANALYSIS

According to the forecasting results and their errors analysis, we discuss the above experiments as follows.

1) Firstly, the proposed method is applied to the field of finance. The TAIEX is recorded every day and fluctuates wildly. It is divided into groups by year because there are too many data values and they experience such a long time. As can be seen from Table 1, the proposed method has the best prediction accuracy by the measurement of *RMSE*, both in each group and overall average. Besides, in SBI share price forecasting, our method also has the minimum value of *RMSE*. Therefore, it is believed that our method is applicable to financial time series prediction.
2) CCI is an significant indicator in construction industry. As shown in Fig. 7, the CCI data show an increasing trend on the whole, but vary a lot from month to month. The proposed method requires at least two values to make a prediction for the first step, so the first two data values are adopted. Table 1 lists the errors of each method. Although it seems that the accuracy has only improved a little by the proposed method, it may save a lot of costs when applied to huge construction projects. The R value (0.9998) is so close to 1, indicating that the proposed method has achieved high correlation.
3) Like CCI prediction, the first two values of enrollment are first input to obtain the third data value. All the forecasting results will be calculated by repeating the first step. As shown in Fig. 10, the predicted values (red curve) are close to the actual ones (black curve). Meanwhile, the proposed method also shows a better predictive accuracy than other four methods. The accurate prediction of enrollment for the next year helps school to go in normal operation.

V. CONCLUSION

In this paper, based on the analysis of complex network, a novel method for time series forecasting is proposed. Firstly, the time series is transformed into a network by visibility graph. This provides a new point of view to study on time series based on complex network theories. Besides, the link prediction method is applied to explore potential links between two nodes. The node with highest similarity index and the last observed node are directly linked to predict y_{N+1}.

The node distance is also a crucial factor in the network, so it is adopted for weight determination. The further node (t_M, y_M) is away from node (t_N, y_N), the more previous information it carries. Consequently, the weight coefficient of initial prediction results, i.e. w_{N+1}, becomes larger while w_N gets smaller accordingly.

The proposed method takes full advantages of the properties of the nodes themselves in the network, inheriting the characteristics of time series. It is on the basis of such analyses that the improved forecasting model is constructed. In order to fully demonstrate effectiveness of the proposed method, we adopt some classic time series datasets. Compared with other models and methods, the proposed method achieves more accurate prediction. It is convince that our method is applicable to finance, construction industry, and some other fields.

Although the proposed method has a good prediction performance, it also can be improved in many aspects. For example, the data mining method can be used to deal with the time series data sets before mapped into the network. It may help to construct a more better network and further improve the prediction accuracy. We will focus on this work in the future.

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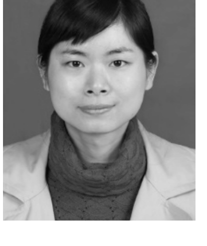

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