Financial Engineering and Risk Management (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/ferm.2023.061126
ISSN 2523-2576 Vol. 6 Num. 11

Systematic Risk Stress Prediction in Bond Market Based on EEMD-LSTM

Zongxuan Chai[a], Tingting Zheng[*]

School of Electrical and Control Engineering, North China University of Technology, Beijing, 100144, China
[a]21101150110@mail.ncut.edu.cn
[*]Corresponding author: zhengtt2019@ncut.edu.cn

Keywords: Systemic risk; Bond Markets; Ensemble Empirical Mode Decomposition; Long Short-Term Memory

Abstract: Forecasting financial systemic risk has always been an important element of financial research. Despite being a key component of our country's financial market, the bond market has received relatively less systematic research attention from scholars in terms of singular market risk warnings. This paper draws on established research to construct a systemic risk stress index for the bond market. Innovatively, it utilizes the Empirical Mode Decomposition (EEMD) method to decompose the pressure index of the Chinese bond market from 2010 to 2023 into individual IMF sequences. Then, it employs the LSTM algorithm for ensemble forecasting, conducting systematic risk warning research. According to the simulation results, China's bond market will show a trend of declining pressure or low pressure in the long term, and the systemic risk will fluctuate less under effective regulation. Meanwhile, the EEMD-LSTM model has higher risk prediction accuracy compared with single LSTM model prediction.

1. Introduction

China has entered a new stage of high-quality economic development, and the report of the 20th Party Congress of the Communist Party of China calls for holding the bottom line of no systemic risk in the financial system, while the prediction of financial systemic risk pressure is an important theme of financial research. Bond debt financing is an important financing method for enterprises in China, as of 2022, China's bonds have been the world's second-largest bond market, with a huge market size and risk spillover effect, easy to make their own risk of volatility across the market contamination [1] As a result, the monitoring of systemic risk in bond markets has become increasingly important. Illing and Liu (2003)[2] proposed to construct a financial stress index to reflect the overall systemic risk level, and the measure has been widely recognised since its introduction. Balakrishnan et al. (2011)[3], Tao and Zhu (2016)[4], Li and Liang (2020)[5] and many other scholars use this to construct a multi-dimensional index system to measure the risk pressure of various sub-markets, which makes the system of financial market systemic risk measurement system more complete. Single bond market Wu et al. (2018) [6] used factor analysis to establish China's bond market vulnerability index to test the transmission mechanism of multi-market factors for the bond market. Zhao et al. (2022)[1], on the other hand, measured the level of systemic risk in China's bond market based on principal component analysis, but at present, the systemic risk measurement index of single bond market is not uniform, and less attention is paid to the early warning research of systemic risk in bond market.

Currently, time series data forecasting research is mainly based on traditional econometric models such as ARMA, however, it is more difficult to deal with time series with nonlinear, non-smooth and other complex characteristics. Deep learning algorithms do not need to be based on strict data requirements and the premise of hypothetical testing and have better prediction results by scholars are widely concerned. In deep learning, the recurrent neural network (RNN) [7] is embedded within a self-feedback, recurrent network structure to further portray the backward and forward dependence of the time series [8]. The Long Short-Term Memory neural network algorithm (LSTM) further improves its long-term dependence problem [9] and becomes the main method for predicting time series models nowadays. Due to the high noise characteristics of financial time series data, Huang et al. (1998)[10] proposed empirical modal decomposition (EMD) to improve the setting problem of the past wavelet decomposition methods by decomposing the sequence through certain rules, and Wu, Z. and Huang (2009)[11] further proposed that the EEMD algorithm helps to extract the real modal components by adding white noise to the original time-series data, and by averaging them many times, the noise cancels out each other, which can effectively avoid the phenomenon of modal mixing to make the prediction performance further improved. At present, scholars such as Tang et al. (2022) [12] initially use EEMD-LSTM to conduct early warning research on systemic risk in the insurance industry.

Combining the above studies, this paper constructs pressure indexes based on systemic risk pressure in bond market through entropy weighting method, decomposes the original sequence of bond pressure indexes using EEMD algorithm, predicts and models each sub-sequence separately using deep learning algorithm of LSTM, and finally integrates early warning research on China's bond systemic risk.

2. Model construction

2.1 The entropy weight method (EWM)

As the selection of single bond market dimension risk pressure index has not yet formed a unified conclusion at this stage, this paper refers to Li et al.'s study(2022) [13], which selects bond index volatility, credit spreads and term spreads to construct a comprehensive risk pressure index (BSI). The volatility of the bond index is measured by the new composite net price (total value) index of China Bond. Credit spreads are constructed by taking the difference between the spot yield of 10-year AAA-rated Chinese corporate bonds and the spot yield of treasury bonds. The term spread is the difference between the spot yield of 10-year treasury bonds and the spot yield of 1-year treasury bonds to construct a negative indicator. In this paper, EWH is used to measure the composite indicators: generalised standard processing based on data, calculation of entropy value of each indicator and then calculation of weights, weighting to calculate the final indicator[1].

2.2 Ensemble Empirical Mode Decomposition (EEMD)

In this paper, we refer to Wang's improved EEMD algorithm for sequence data decomposition, and the specific decomposition setting model is:

[1] EWH has now been used as a more mature indicator measurement method, limited to the length of the article, this paper will not be redundant elaboration.

$$x_i(t) = x(t) + n_i(t) \quad (1)$$

$$x_i(t) = \sum_{s=1}^{S} L_{is}(t) + r_{is}(t) \quad (2)$$

$$L_s(t) = \frac{1}{M}\sum_{i=1}^{M} L_{is}(t) \quad (3)$$

In the above equation, Eq.(1) adds normally distributed white noise ni(t) to the original signal x(t) i times to generate a new signal xi(t). Secondly for the new signal the EEMD decomposition is performed to obtain the IMF component, Lis(t) denotes the sth IMF obtained by adding white noise decomposition for the ith time, ris(t) denotes the residual function, and s denotes the number of IMFs. Repeat steps 1 and 2 M times to obtain a series of IMF components for each decomposition, and then average the corresponding IMF components obtained each time to obtain the final EEMD decomposition result. where Eq. (3) Lis (t) denotes the sth IMF of the EEMD decomposition, i=1,2... .M, s=1,2,... .S.

2.3 Long Short-Term Memory (LSTM)

LSTM adds memory vectors to the RNN network and introduces a gating mechanism to solve problems such as RNN gradient explosion. The whole consists of cell state, forget gate, input gate and output gate, so as to control the forgetting and updating of sequence data, the specific structure is shown in Figure 1.

The specific algorithmic flow of LSTM is described by Eqs. (4)~(9), which is limited to the length of the article and will not be elaborated too much.

$$I_t = \delta(W_{xi}x_t + W_{ui}y_{t-1} + b_i) \quad (4)$$

$$\widetilde{D} = tanh(W_{xD}x_t + W_{hD}y_{t-1} + b_D) \quad (5)$$

$$O_t = \delta(W_{xo}x_t + W_{uo}y_{t-1} + b_o) \quad (6)$$

$$F_t = \delta\left(W_{xf}x_t + W_{uf}y_{t-1} + b_f\right) \quad (7)$$

$$D_t = F_i \times D_{t-1} + I_t \times \widetilde{D} \quad (8)$$

$$h_t = O_t \times tanh(D_t) \quad (9)$$

Ft, It, Ot represent the forget gate, input gate, and output gate at time t. xt, yt, $\widetilde{D}$, Dt represent the input value, output value, update gate, and final cell state. δ, tanh represent the activation function. W, b represent the weight matrix and error, and ht is the output of the LSTM network.

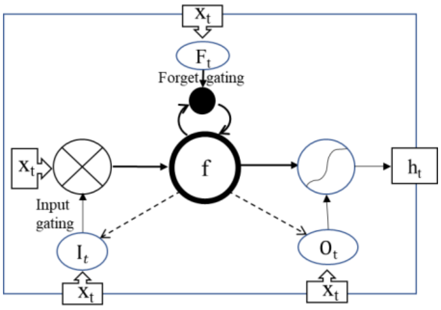


Figure 1: LSTM algorithm structural framework

2.4 EEMD-LSTM

This paper draws on the TEI@I complex methodology[14] with Chen (2021)[15] and other scholars to construct the EEMD-LSTM model to early warn the systemic risk of China's bond market, and the structure of its detailed modelling process is shown in Figure 2.

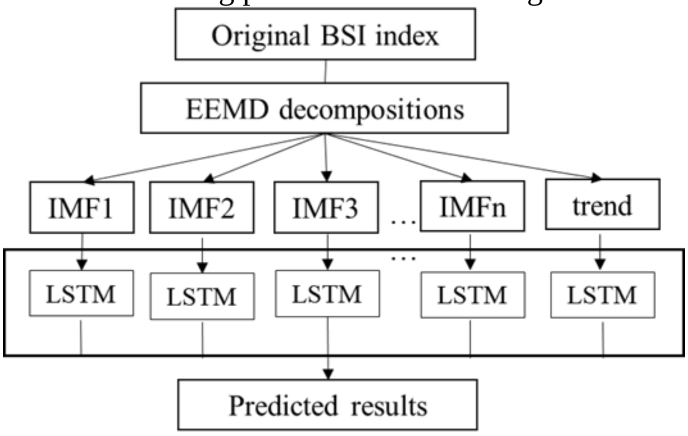


Figure 2: EEMD-LSTM algorithm structural framework

In Figure 2, the BSI index sequence to be analysed is subjected to empirical modal decomposition to obtain a total of 7 components and residual terms for each component (IMF1, IMF2, ..., IMFn) after decomposition. Then the LSTM prediction model is built for all the components and trend terms, and the prediction is performed, and the final prediction is obtained by aggregating the predicted values.

3. Simulation analysis

3.1 Indicator construction and EEMD decomposition

In this paper, the BSI indicator constructed with the bond market data from 4 January 2010 to 5 December 2023 is used for simulation and early warning analysis. Due to the high noise of single-day financial data, this paper constructs indicators in the initialisation process for weekly mean processing, the final indicator data for the weekly mean series, the specific results are shown in Figure 3. According to the results of the indicators can be seen in 2011, China's bond industry in the second half of the year the overall risk of the pressure to reach the peak, speculation may be related to the year's new issuance of treasury bonds to Hong Kong and the monetary policy, the overall pressure tends to decline year by year, visible bond market Systemic risk has been effectively controlled as China's financial market regulation improves and becomes increasingly stable.

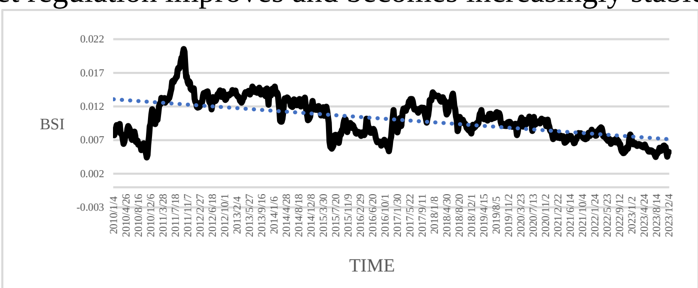


Figure 3: The BSI index.

According to the non-equilibrium and non-stability of the data, this paper carries out the EEMD decomposition to sequentially separate out the 7 groups of IMF components from high to low frequency and the overall residual term RES, so as to improve the accuracy of further LSTM prediction, and the decomposition results are shown in Figure. 4.

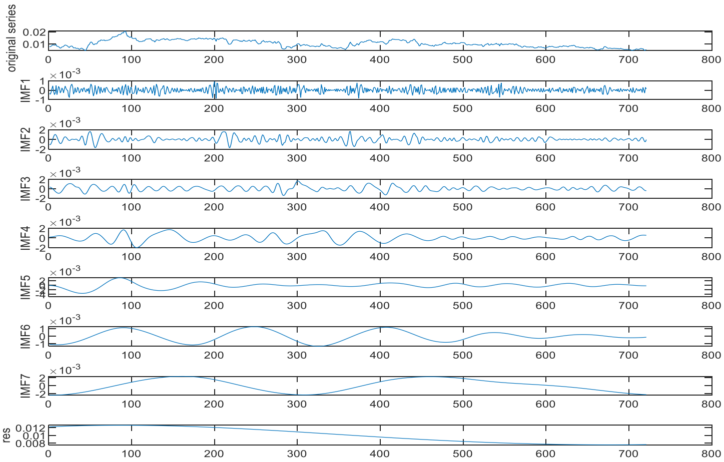
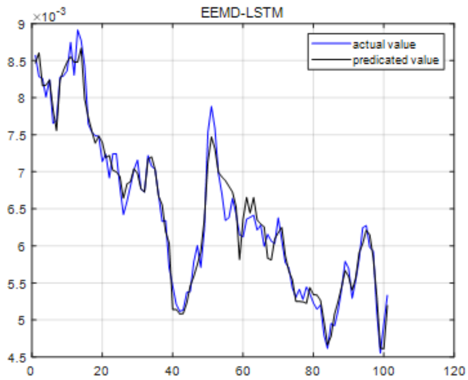


Figure 4: EEMD decomposition results

3.2. The prediction results of EEMD-LSTM

Before performing the LSTM network analysis, in order to reduce the bias of the results, the individual IMF components are normalised in this paper. The specific method is general data normalisation, which is not repeated here. In this paper, on the sample setting, the first 70% of the proportion of the sample is set as the training set, and the last 30% of the data is set as the test sample, and 200 hidden layer neurons are set to carry out rolling prediction of specific dimensions to meet the modelling requirements. In order to make the simulation results interpretable, this paper carries out the inverse normalisation process for the predicted fitted data, which makes its predicted data close to the real data and improves the interpretability of the simulation results. In order to further verify the prediction effect of EEMD-LSTM with and without EEMD decomposition, this paper compares the LSTM prediction results of the sequence data directly with the EEMD-LSTM results, and the specific results are shown in Figure 5.



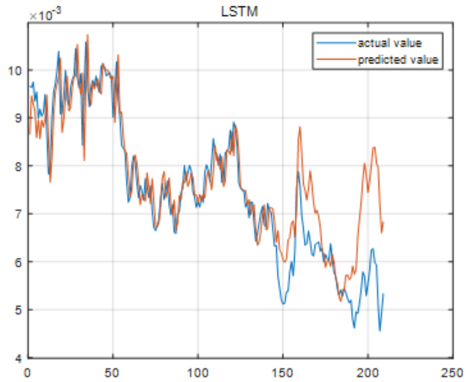


Figure 5: Comparison of EEMD-LSTM and LSTM results

As can be seen from the figure, the goodness-of-fit of bond market systematic risk prediction after performing empirical modal decomposition is significantly higher than that of direct LSTM algorithm prediction. Therefore, through the EEMD decomposition can effectively reduce the serial data complexity of the original BSI indicator, and then further adopt the deep learning LSTM algorithm risk prediction, which can effectively improve the prediction accuracy. Based on the prediction results, it can be seen that the systemic risk pressure in China's bond market will probably present a low-pressure state, the risk pressure is small, but need to continue to pay attention.

4. Conclusions

Based on China's bond market data, this paper measures the systemic risk of China's bond market by constructing a systemic risk stress index, and predicts the future trend of the stress index through the EEMD-LSTM deep learning algorithm to achieve an early warning effect, and draws the following conclusions from the empirical analysis:

The systemic risk stress index of China's bond market constructed in this paper reflects that the systemic risk faced by China after 2010 reached a peak in 2011 and then continued to decline, which is consistent with the current operating conditions of China's bond industry and can measure the systemic risk situation of China's bond market.

This paper adopts the improved EEMD signal decomposition method based on EMD to decompose the bond market stress index, which can improve the prediction effect based on LSTM algorithm. The EEMD-LSTM model constructed in this paper can effectively play the advantage of empirical modal decomposition on the processing of complex time series data, further improve the LSTM prediction accuracy, and can be applied to the early warning of systematic risk in China's financial market, compared with the direct LSTM risk prediction.

References

[1] Zhao, W.; Meng, X.; Xiang, X. Research on the Mechanism and Measurement of Systemic Risk Formation in China's Bond Market. Journal of Financial Development Research 2022, 10, 82-87.

[2] Illing, M.; Y, Liu. Measuring Financial Stress in a Developed Country: an Application to Canada. Journal of Financial Stability 2006, 2(3), 243-265.

[3] Balakrishnan, R.; Danninger, S.; Tytell, I. The Transmission of Financial Stress from Advanced to Emerging Economies. Emerging Markets Finance and Trade 2011, 47, 40-68.

[4] Tao, L.; Zhu, Y. On China's Financial Systemic Risks. Journal of Financial Research 2016, 6, 18-36.

[5] Li, M.; Liang, S. Monitoring Systemic Financial Risks: Construction and State Identification of China's Financial Market Stress Index. Journal of Financial Research 2021, 6, 21-38.

[6] Wu, H.; Han, Y.; Zheng Z. An Experimental Construction of the Monitoring System of Bond Market Fragility in China. Financial Regulation Research 2018, 6, 31-47.

[7] Li, X.; Zhao, G.; Wang Y. Improved Internet of Things Intrusion Detection Model for CNN and RNN. Computer Engineering and Applications 2023, 59(14), 242-250.

[8] Elman, J. L.Finding Structure in Time. Cognitive Science 1990, 14(2), 179-211.

[9] Hochreiter, S.; Schmidhuber, J. Long short-term memory. Neural Computation 1997, 9(8), 1735-1780.

[10] Huang, N E.; Shen, Z.; Long, S R.; et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences 1998, 454(1971), 903-995.

[11] Wu, Z.; Huang, N E. Ensemble empirical mode decomposition: a noise-assisted data analysis method. Advances in Adaptive Data Analysis 2009, 1(1), 1-41.

[12] Tang, Z.; Wu, J.; Zhang, T.; et al. An EEMD-LSTM Model Based Research on Early Warning of the Systematic Risk in China Insurance Industry. Management Review 2022, 9, 14.

[13] Li, Z.; Fang, M.; Zhang, M. Research on the Cross-Market Spillover Effect of Financial Stress in China——From the Perspective of Systemic Risk Management. Financial Forum 2022, 27(8), 7-18.

[14] Wang, S.; Yu, L.; Lai, K. TEl@I Methodology and Its Application to Exchange Rates Prediction. Chinese Journal of Management 2007, 1, 21-27.

[15] Chen, Y.; Dong, Z.; Wang, Y.; et al. Short-term wind speed predicting framework based on EEMD-GA-LSTM method under large scaled wind history. Energy Conversion and Management 2021,227, 113559.