

Predicting Bitcoin Prices Using Time Series Chaotic Neural Oscillatory Networks (TSCNON) in Quantum Finance

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Abstract. Traditional financial prediction models are difficult to cope with complex financial markets, especially cryptocurrency markets. In this paper, a quantum finance-based temporal chaotic neural oscillatory network (TSCNON) prediction model is used for the first time to predict the share price of Bitcoin by combining the quantum price level (QPL) technique with the theory of chaotic neural networks. Based on quantum field signalling (QFS) and Lee oscillator, the overfitting and deadlocking problems of traditional neural networks when dealing with large-scale financial data are solved. The structural design of the TSCNON model and its training algorithm are presented. The application framework of TSCNON in Bitcoin price prediction is demonstrated. Experimental results show that the TSCNON model can greatly reduce the prediction error and improve the prediction accuracy. This paper provides financial market participants with more accurate and reliable prediction tools and promotes the promotion of quantum financial technology in practical applications.

1 Introduction

Financial market forecasting has always been a focus of both academic and practical attention. With the continuous development and complexity of the global financial market, especially the rise of the cryptocurrency market, the volatility of the financial market has increased significantly, and the traditional forecasting methods have gradually revealed their limitations. Quantum finance, as an emerging interdisciplinary field, provides new ideas and technical means for predicting financial markets. The Quantum Price Level (QPL) technique models price fluctuations in financial markets using the principles of quantum mechanics, which can more accurately capture the intrinsic laws of the market. However, it is difficult to achieve real-time prediction of financial markets by relying solely on QPL technology. Chaotic neural networks (CNNs), as a tool capable of dealing with complex dynamic systems, have good adaptive and overfitting resistance. Therefore, this paper proposes a time-series chaotic neural oscillatory network (TSCNON) model that combines quantum price level technology and chaotic neural networks to improve the prediction accuracy and reliability of financial markets. By introducing quantum field signals (QFS) and improved neural

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oscillators (Lee oscillators), the TSCNON model is able to effectively solve the overfitting and deadlock problems of traditional neural networks when dealing with large financial data, and provide financial market participants with more accurate and reliable forecasting tools.

2 Literature Review

In recent years, Bitcoin price prediction has become a hot research topic in academia and investment community due to its high volatility and potential high returns . Although several traditional time series models have been developed, they are limited to modelling stationary time series and are difficult to find well when the time series have chaotic characteristics such as those of the cryptocurrency market [1]. Therefore, many researchers have attempted to use machine learning (ML) and deep learning (DL) techniques to predict the price of Bitcoin [1]. Recurrent neural networks (RNNs) is a significant class of artificial neural networks which are employed to model time-series processes [2]. LSTM is a type of Recurrent Neural Network (RNN) that has been shown to learn long-term dependencies and has been successfully applied in a number of fields [3]. Jang and Lee compared the performance of deep neural networks (DNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs) in the context of Bitcoin price prediction [4]. The results in their study demonstrated that LSTMs exhibited superior performance in price regression prediction when compared with DNNs and CNNs. However, DNNs demonstrated a higher level of efficacy in price trend classification [4]. Bâra and Oprea presented a hybrid model incorporating CNN and BiLSTM and optimised through a meta-heuristic algorithm to predict Bitcoin prices. Erfanian et al. attempted to utilise high-dimensional feature for short- and medium-term prediction of Bitcoin price and next-day prediction accuracy rate was about 65% [5]. Many studies have also shown that deep learning can be used to capture the nonlinear dynamics of complex time series by combining market sentiment and blockchain data, and different algorithms such as support vector machines and random forests can be used to improve the prediction accuracy [6-12].

The chaotic nature of the cryptocurrency market motivates researchers to explore the application of chaotic neural networks in predicting its price. To detect the fractal and self-similar patterns of time series, some researchers used deep learning-based chaotic neural networks to predict the price of Bitcoin, Digital Cash, and Ripple [13, 14]. And some compared the performance of RNNs and different reservoir computing techniques for the prediction of chaotic time series [15]. They pointed out that RNNs and reservoir computing techniques perform excellently in both short-term and medium-term predictions. These results indicate that the nonlinear dynamics of financial markets can be modelled by chaotic neural networks, which lays a theoretical basis for the TSCNON model. With the emergence of quantum finance, quantum predictive models are also revitalised. For example, Emmanoulopoulos and Dimoska presented an application of parameterised quantum circuits as quantum neural networks for the prediction of financial time series [16]. They claimed that the quantum neural network outperforms classical BiLSTM model in describing financial time series with high noise using fewer numbers of model parameters. Although the current hardware and algorithm of quantum computing are still under development, it provides a new technical support for the quantum-enhanced TSCNON. Recently, Wei et al. proposed a deep learning and network representation learning method, named as DLForecast, which can capture the spatio-temporal patterns of Bitcoin transaction and improve the prediction of Bitcoin transaction [17, 18].

This paper employs a time series prediction method proposed by Lee, called TSCNON, which combines chaotic neural oscillation networks with quantum computing. The primary motivation behind TSCNON is to model the nonlinear dynamics of Bitcoin prices and leverage quantum computing for efficient data processing, thereby providing more accurate

Bitcoin price predictions. To the best of our knowledge, this is the first instance of combining chaotic neural oscillation networks with quantum computing for time series prediction. The contributions of this paper are summarised as follows: 1) We pioneered the use of TSCONON in the field of cryptocurrency, expanding the scope of existing prediction methods. 2) Numerical results demonstrate that TSCONON can effectively capture the chaotic behaviour of time series and provide more accurate prediction results. 3) TSCONON offers a new direction for financial product price prediction. Combining the advantages of these two fields holds great potential for further improving prediction performance.

Existing researches show that deep learning models have some significant advantages in dealing with complex time series problems [20]. In addition, chaotic neural networks can also model the nonlinear pattern of markets. Recently, quantum finance provides technical support for TSCONON in dealing with high-noise data [16]. For example, Khaniki et al. combined Transformers with BiLSTM to improve the temporal dynamics and localisation of the time series, which also shows a promising direction for hybrid model in cryptocurrency prediction. It is hypothesised that TSCONON will be capable of modelling the chaotic behaviour of Bitcoin prices through oscillatory networks and leveraging quantum computing to accelerate prediction.

3 Methodology

3.1 Quantum Price Level (QPL)

First, the Daily Price Return (DR) is calculated, defined as,

$$DR[d] = \frac{DC[d]}{DR[d+1]} \quad (1)$$

where $(DC[d])$ denotes the closing price on day (d) .

Next, the Lambda value (λ) is computed by solving the quantum price return wave function $(Q(r))$ using the finite difference method (F.D.M.).

$$\lambda = \left| \frac{r_{-1}^2 \varphi_{r-1} - r_{+1}^2 \varphi_{r+1}}{r_{+1}^4 \varphi_{r+1} - r_{-1}^4 \varphi_{r-1}} \right| \quad (2)$$

where (φ_{r-1}) and (φ_{r+1}) are the normalized wavefunction values of the adjacent points. This λ value is used to solve for the quantum financial energy level $(E(n))$ using Cardano's formula,

$$E(n) = \sqrt[3]{-\frac{q}{2} + \sqrt{\frac{q^2}{4} + \frac{p^3}{27}}} + \sqrt[3]{-\frac{q}{2} - \sqrt{\frac{q^2}{4} + \frac{p^3}{27}}} \quad (3)$$

Among them,

$$p = -(2n + 1)^2, \quad q = -\lambda(2n + 1)^3 [K_0(n)]^3 \quad (4)$$

And,

$$K_0(n) = \left[\frac{1.1924 + 33.2383n + 56.2169n^2}{1 + 43.6196n} \right]^{1/3} \quad (5)$$

Through this process, the top 21 quantum financial energy levels (QFEL) are calculated. From the QFEL, the quantum price return (QPR) is calculated,

$$QPR(n) = \frac{QFEL(n)}{QFEL(0)} \quad (6)$$

Finally, the Normalized Quantum Price Return (NQPR) is calculated,

$$NQPR(n) = 1 + 0.21 \times \sigma \times QPR(n) \quad (7)$$

where σ is the standard deviation of the wave function.

The NQPR value is used as the QPL value to provide potential support and resistance levels for Bitcoin price predictions. These QPL values are used as input features together with historical price data in the TSCNON model.

3.2 Lee Oscillator in Chaotic Neural Networks

Lee oscillator is a chaotic neural oscillator firstly proposed by Lee. It has been shown that this kind of oscillator is suitable for modelling the dynamic properties of financial markets [2]. In this paper, Lee oscillators are embedded in the hidden layer of TSCNON to process time series data and QPL are used to predict bitcoin price series.

The update of the state of the Lee oscillator at time (t) is described by the following equation:

$$E(t+1) = \text{Sig}[e_1 \cdot E(t) - e_2 \cdot I(t) + S(t) - \xi_E] \quad (7)$$

$$I(t+1) = \text{Sig}[i_1 \cdot E(t) - i_2 \cdot I(t) - \xi_I] \quad (8)$$

$$\Omega(t+1) = \text{Sig}[S(t)] \quad (9)$$

$$L(t) = [E(t) - I(t)] \cdot e^{-kS^2(t)} + \Omega(t) \quad (10)$$

3.3 Time Series Chaotic Neural Oscillatory Network (TSCNON)

The training process of TSCNON consists of forward propagation and back propagation. The forward propagation calculates the output of each layer, utilizing the Lee oscillator dynamics. First, the input of the hidden layer Lee oscillator is calculated:

$$\overline{L_{\text{Hinput}}} = \sum_{n=0}^{40} \overline{L_{\text{In},n}} \overline{\omega_n} \quad (10)$$

Where $\overline{L_{\text{In},n}}$ is the output of the input layer Lee oscillator and $\overline{\omega_n}$ is the weight. The hidden layer Lee oscillator updates its state according to the above equation ($E(t+1)$) to $L(t)$. Next, the input to the output layer Lee oscillator is computed:

$$\overline{L_{\text{Oinput}}} = \sum_{m=0}^{40} \overline{L_{\text{Hm}}} \overline{\omega_m} \quad (11)$$

where $\overline{L_{\text{Hm}}}$ is the output of the hidden layer Lee oscillator. The output layer Lee oscillator produces the predicted price (L_O).

Back propagation adjusts the weights to minimize the prediction error. The error of the output layer is computed as:

$$\overrightarrow{\delta_{HO}} = (L_O - \tilde{L}_O) \odot f'_{L_O}(\overrightarrow{L_{\text{Oinput}}}) \quad (12)$$

where \tilde{L}_O is the actual price and (f'_{L_O}) is the derivative of the activation function. The error in the hidden layer is:

$$\overrightarrow{\delta_{IH}} = (\sum \overrightarrow{\delta_{HO}} \cdot \overline{\omega_{HO}}) \odot f'_{L_H}(\overline{L_{\text{Hinput}}}) \quad (13)$$

The weights are updated as follows:

$$\overline{\Delta\omega_{IH}} = \beta \overrightarrow{\delta_{IH}} \overline{L_{IH}^T}, \quad \overline{\Delta\omega_{HO}} = \beta \overrightarrow{\delta_{HO}} \overline{L_H^T} \quad (14)$$

where (β) is the learning rate. Finally, the weights are updated as:

$$\overline{\omega(t+1)} = \overline{\omega(t)} + \overline{\Delta\omega(t)} \quad (15)$$

This process is repeated until the prediction error is minimized. The model is implemented in a Python environment, using standard machine learning libraries to support development and optimization.

4 Empirical results

4.1 Data Sources and Processing

The data used to predict the May price of Bitcoin was sourced from a financial platform (AvaTrade) covering historical price data from 2015/1/2-2025/1/2 using weighted price. This data, along with the QPL computed via the QFSE, was cleaned to remove missing values or outliers to ensure data integrity. The data were then normalised to the $[0,1]$ interval to fit the neural network inputs. Feature selection consisted of a 5-day time series and 20 QPLs, balancing model complexity and predictive power.

4.2 Model Performance Evaluation

The model performance evaluation results are summarised in Table 1 and visualised in the figure 1. The table compares the performance of the LSTM and TSCNNON models in terms of mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean determination coefficient (R^2).

Table 1. Comparison of model performance evaluation

Model	Average MSE	Average RMSE	Average MAE	Average R^2
LSTM	0.0030	0.0535	0.0296	0.9345
TSCNON	0.0027	0.0518	0.0245	0.9393

The TSCNON model successfully captures complex and non-linear patterns in financial time series by integrating quantum financial signals and the chaotic properties of the Lee oscillator. The quantum financial signals help the model deal with market volatility. The chaotic nature of the Lee oscillator effectively simulates abnormal behaviour in financial markets, especially in highly volatile assets such as bitcoin. TSCNON can handle non-stationary time series data, a feature that gives the model significant advantages in financial market forecasting.

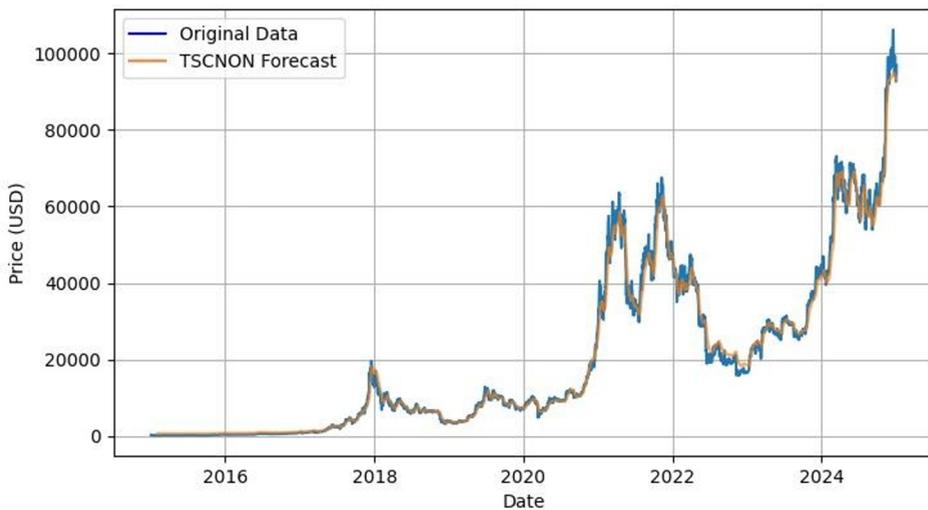


Fig. 1. Bitcoin Price Prediction Performance of Quantum-Enhanced LSTM Models

5 Conclusion

we predicted the short- and medium-term prices of bitcoin (BTC) using a novel hybrid model, the time-series chaotic neural oscillation network (TSCNON) model, in conjunction with quantum price level (QPL) technology. We compared the performance of TSCNON with other traditional machine learning models. The results indicate that TSCNON outperforms other models. The results indicate that the TSCNON algorithm significantly outperforms the existing literature in predicting daily closing prices and price rise/fall. Moreover, it is able to capture the chaotic and non-linear dynamics of bitcoin prices.

This is the first study to apply quantum finance and chaotic neural networks to predict cryptocurrency prices. Future work could investigate how to optimise the TSCNON architecture to identify more complex market anomalies and trends.

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