

Deep hybrid models for bitcoin forecasting: EMD, CEEMDAN, and LSTM in comparison

Ayoub Aarabi, Maryem Ait Moulay, Issam Bouganssa, Abdelali Lasfar

Laboratory Systems Analysis, Information Processing, and Industrial Management, High School of Technology Salé,
Mohammed V University in Rabat, Rabat, Morocco

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ABSTRACT

In this study, an artificial neural network (ANN) was developed to forecast Bitcoin prices using one of the most successful deep learning architectures for time series analysis: long short-term memory (LSTM) networks. This model was enhanced with a signal processing layer that reduces the impact of the instrument's high volatility on prediction accuracy by applying two signal decomposition techniques: empirical mode decomposition (EMD) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN). This study is motivated by the major fluctuations in Bitcoin prices, which make precise forecasting difficult but crucial for experts and investors. This findings demonstrate that forecasting performance improves when decomposition techniques are used. In particular, compared to the conventional LSTM and EMD-LSTM models, the CEEMDAN-LSTM model achieved the highest accuracy, with a mean absolute error (MAE) of 167.837 and a root mean square error (RMSE) of 255.673, outperforming both EMD-LSTM (MAE =168.785, RMSE =256.042) and the standard LSTM (MAE =169.516, RMSE =256.225). The combination of CEEMDAN and LSTM results in a more reliable model that can accurately capture short-term fluctuations in Bitcoin prices.

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Corresponding Author:

Ayoub Aarabi

Laboratory Systems Analysis, Information Processing, and Industrial Management

High School of Technology Salé, Mohammed V University in Rabat

Rabat, Morocco

Email: ayoub.arb@gmail.com

1. INTRODUCTION

The New York Stock Exchange (NYSE), the world's largest stock exchange, is currently considering a transition toward extended or even continuous trading hours. This shift reflects broader changes in global financial markets, where cryptocurrencies, led by Bitcoin, have introduced a model of uninterrupted trading. In this context, traditional market structures may appear increasingly misaligned with continuously operating digital-asset environments. Bitcoin was introduced by Nakamoto in a seminal white paper published in 2008 [1], with the objective of enabling a decentralized digital payment system without reliance on intermediaries. It is based on blockchain technology, which ensures transparency and resistance to tampering through a proof-of-work consensus mechanism [2], [3]. Each participant in the network maintains a complete copy of the transaction ledger, ensuring robustness, verifiability, and transparency [4].

Initially regarded with skepticism, Bitcoin has experienced significant growth, with its market

capitalization surpassing \$1 trillion in recent years and increasing institutional adoption. It is now often considered a potential safe-haven asset, comparable to gold [5], and a hedge against inflationary pressures and expansionary monetary policies [6]. Some countries, such as El Salvador and the Central African Republic, have adopted Bitcoin as legal tender or incorporated it into national reserves [7]. At the same time, major central banks, including the European Central Bank and the People's Bank of China, are exploring the development of central bank digital currencies (CBDCs) [8], [9]. This growing recognition highlights the strategic importance of cryptocurrencies and motivates further investigation into their volatile dynamics. Unlike traditional financial assets, cryptocurrency prices are influenced by a combination of technological, macroeconomic, and behavioral factors, which makes their modeling particularly challenging [10]. In this context, developing reliable forecasting models, especially those based on deep learning, has become an important scientific and economic issue.

2. RELATED WORKS

Price prediction of cryptocurrencies is an inherently difficult task, because it involves forecasting future values of a long and highly volatile financial time series. This complexity is the result of very high volatility of cryptocurrency-based financial time series, which are influenced by economic, political, technological, and psychological forces. Such series are typically non-stationary and nonlinear, and are frequently exposed to exogenous shocks. To address the limitations of the classical methods that fail to capture the dynamics of these series, many recent studies rely on deep learning approaches.

In this regard, Derbentsev *et al.* [11] investigated the short-term dynamics of Bitcoin, Ethereum, and Ripple using sophisticated algorithms including artificial neural networks (ANNs), random forests (RFs) and binary autoregressive trees (BARTs). They found that both ANN and BART models substantially outperformed naive classification methods (up to 63% accuracy out-of-sample) based on more than 1,500 daily observations between 2015 and 2019. Chowdhury *et al.* [12] continued with a larger number of cryptocurrencies, including the CCI30 index, and used more advanced machine learning models as boosted trees, k-nearest neighbors, and robust ensemble models. The authors' research for the years 2017 to 2019 showed that their ensemble models and their boosted tree methods performed very well, surpassing even several sophisticated models.

However, multiple studies have since underscored the inherent limitations of deep learning models when they are applied to this kind of time series. Pintelas *et al.* [13] showed that long short-term memory (LSTM)- or convolutional neural network (CNN)-based models can be powerful, their performance degrades in the presence of noise and missing data. For a more robust prediction and a prediction with a higher reliability, Livieris *et al.* [14] introduced ensemble architectures using bagging, stacking, and averaging methods involving sets of several LSTM and Conv1D learners on hourly data for Bitcoin, Ethereum, and Ripple. The obtained results suggest that the hybrid models, though computationally expensive, exhibit large margins in accuracy.

In a similar, more specific manner, Patel *et al.* [15] proposed a hybrid LSTM-gated recurrent unit (GRU) model for Litecoin and Monero price prediction. The results of experiments demonstrate that this recurrent model could obtain better results when comparing with the simple LSTM networks, especially in terms of root mean squared error (RMSE) and mean absolute percentage error (MAPE). Other studies, such as in [16], [17], emphasized the importance of explanatory variable selection, employing methods such as the granger causality, mutual information, and grey relational analysis (GRA) to quantify the influence of macroeconomic variables on Bitcoin price. More recent works have compared deep hybrid models to the traditional approaches. Chauhan *et al.* [18] considered a CNN-GRU model for long horizon prediction in the Bitcoin price and found that deeper network structures do not necessarily lead to better performance without proper pre-processing of signals. Similarly, Qureshi *et al.* [19] analyzed some classical (e.g., auto-regressive integrated moving average (ARIMA), multi-layer perceptron (MLP), and extreme learning machine (ELM)) and hybrid models, and they noted that these models are not able to accurately capture the nonlinear dynamics of the cryptocurrency price evolution, especially during the high volatility periods.

However, a major limitation of all these studies is that they have generally preferred to improve the predictive performance by simply exploiting increasingly complex architectures, but they have paid less attention to the solid construction of training sets that are full of contextual information. Nonetheless, adding appropriate exogenous variables, such as oil, gold, interest rates, or dollar strength indexes, can significantly improve the accuracy of forecasts, especially in highly volatile cryptocurrency markets. This gap is addressed in the present study by integrating a fine-grained analysis of basic economic variables, where GRA is employed to

select the most relevant explanatory features and construct an economically informative and coherent input set.

3. METHOD

Forecasting Bitcoin prices is a highly challenging task given the high volatility, non-stationary, and nonlinear nature of the asset [20], [21]. To improve forecasting results under such conditions, a data preprocessing, decomposition, and sequential learning approach was proposed. The general architecture of the proposed methodology is illustrated in Figure 1.

Under this methodology various input variables have been taken into account including open, high, low, close prices, volume traded, and macroeconomic indicators. GRA is used for the determination of the most influential features that share structural similarities with Bitcoin closing price. At the same time, the target variable i.e. the closing price series, would be decomposed using EMD or its improved version known as complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN). This process yields a set of intrinsic mode functions (IMF) and a residual term, where each is associated with a particular frequency component of the signal.

Each IMF and the residue are modeled separately using an LSTM network. These sub-models capture different temporal characteristics and help prevent overfitting to noise. The individual forecasts are subsequently recombined through a reconstruction process to give the final forecast of closing price of the Bitcoin. In addition to short-term volatility reduction, such a modular architecture also enhances the interpretability and robustness of the predictive system. It allows a multi-resolution representation of the market dynamics which reflects the inherent heterogeneity and noisy features of financial time series.

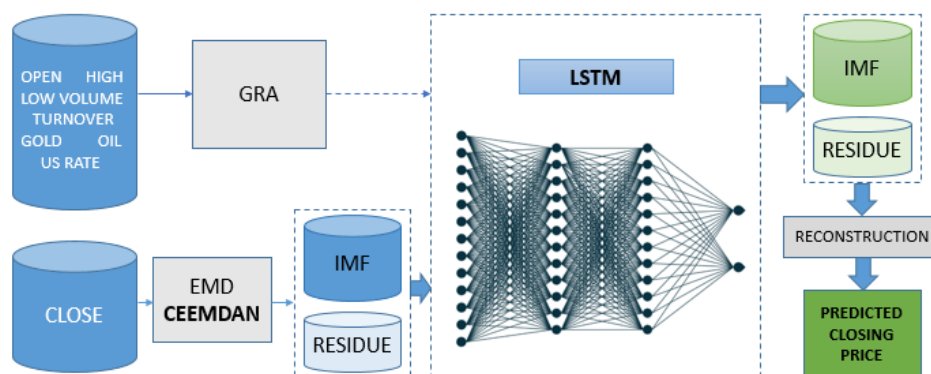


Figure 1. Architecture of our integrated forecasting model

3.1. Experimental setup and reproducibility

The dataset (2014 to 2024, daily) is split chronologically into 70% training (2018 to 2021), 15% validation (2022), and 15% testing (2023 to 2024) to avoid data leakage. One-step-ahead forecasting is performed using a sliding input window of $L = 30$ days. All features are normalized using Min–Max scaling fitted on the training set. Training uses the Adam optimizer (learning rate 10^{-3}) and Huber loss. The LSTM architecture consists of two layers (100 and 32 units) with dropout 0.2 and early stopping. Models are trained for up to 100 epochs with batch size 32. All experiments are implemented in Python using Keras/TensorFlow with a fixed random seed. Both EMD and CEEMDAN decompositions yielded five IMFs in the experiments (with an additional residual component for CEEMDAN). Each component was modeled by an independent LSTM, and the final prediction was obtained by aggregating the forecasts of all components. As summarized in Table 1, the main hyperparameters are reported for reproducibility. In the following, the three forecasting architectures considered in this study are detailed: a benchmark LSTM model, an EMD based hybrid model, and a CEEMDAN-enhanced version.

3.2. Long short-term memory on financial time series

The LSTM neural networks [22] are commonly used for time series predictions tasks, including in financial markets [23], in energy [24] and in cryptocurrencies [25]. They surpass classic neural networks

in situations where memory effects are important as a consequence of their capacity to learn long-term dependencies in sequential data. The memory cell C_t in the LSTM is managed using input i_t , forget f_t , and output o_t gates that enable the information in the cell to be kept or forgotten over time, which makes it ideal for the unpredictable nature of the cryptocurrency market. However, direct application of LSTM to extremely noisy data, e.g., raw Bitcoin prices, may result in overfitting to the noise, causing unstable prediction [26]. At each time step t , given the input x_t , previous hidden state h_{t-1} , and previous cell state C_{t-1} , the LSTM performs computations as in (1) to (6).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (\text{Forget gate}) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (\text{Input gate}) \quad (2)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (\text{Candidate cell state}) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (\text{Cell state update}) \quad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (\text{Output gate}) \quad (5)$$

$$h_t = o_t * \tanh(C_t) \quad (\text{Hidden state}) \quad (6)$$

Here, σ denotes the sigmoid activation function, \tanh is the hyperbolic tangent function, and $*$ denotes element-wise multiplication. These mechanisms allow LSTMs to learn complex temporal dynamics.

Table 1. Main hyperparameters used in the experiments

Component	Setting
Look-back window L	30 days
Forecast horizon	1-step ahead ($t + 1$)
LSTM layers	2
Units per layer	100, 32
Dropout rate	0.2
Optimizer	Adam
Learning rate	0.001
Batch size	32
Epochs	100 (early stopping enabled)
Loss function	Huber loss

3.3. EMD-LSTM: frequency division and multiple levels of representation

To overcome this volatility, we utilize a hybrid approach EMD and LSTM. Huang *et al.* [27] has proposed the EMD, any time series is decomposed into a number of IMFs, all of which correspond to oscillations having different characteristic time scales. Such a decomposition is adaptive and data-driven, and is appropriate for nonlinear and nonstationary signals, and market prices. Each obtained IMF, $c_i(t)$, is presumed to have a higher level of regularity compared to the raw series and in turn easier for modeling. Therefore, the signal can be written as in (7).

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (7)$$

Where $r_n(t)$ is the non-oscillatory residual. Each such component is modeled as independent LSTM and their output are combined to generate the final prediction. This frequency decoupling would make the model very robust in terms of the market state [28]. To capture the subtle frequency patterns embedded in the original Bitcoin price signal, we use the EMD, a data-driven method that decomposes a non-stationary and non-linear time series into a limited set of IMFs. The decomposition algorithm is given in Algorithm 1.

The Algorithm 1 decomposes the original signal adaptively into a finite number of IMFs, each representing a specific local oscillation mode of the original signal. In the case of Bitcoin forecasting, EMD enables the short term fluctuations to be separated from long term trends, making it possible to learn more stable representations of both using separate LSTM models. However, as we will see in the following section, EMD is vulnerable to mode mixing, which drives the need for its improved version.

Algorithm 1 EMD

```

1: Input: Signal  $x(t)$ 
2: Output: Intrinsic mode functions  $\{c_1(t), c_2(t), \dots, c_n(t)\}$  and residual  $r_n(t)$ 
3: Initialize:  $r_0(t) \leftarrow x(t)$ 
4: for  $i = 1$  to  $n$  do
5:    $h_0(t) \leftarrow r_{i-1}(t)$ 
6:   while  $h_k(t)$  is not an IMF do
7:     Identify local extrema of  $h_k(t)$ 
8:     Interpolate upper and lower envelopes
9:     Compute mean envelope  $m_k(t)$ 
10:     $h_{k+1}(t) \leftarrow h_k(t) - m_k(t)$ 
11:   end while
12:    $c_i(t) \leftarrow h_k(t)$ 
13:    $r_i(t) \leftarrow r_{i-1}(t) - c_i(t)$ 
14: end for
15: return  $\{c_1(t), \dots, c_n(t)\}$  and  $r_n(t)$ 

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3.4. CEEMDAN-LSTM: enhanced robustness and mode mixing avoided

However, EMD suffers from mode mixing, a mixing of frequency scales in a single IMF, leading to obstacles to learning. To resolve it, the CEEMDAN method [29] is an enhancement performed to stabilize frequency separation. CEEMDAN introduces white stochastic Gaussian Noise to n copies of the signal in a noise-controlled manner, apply EMD on each n , and averages the decompositions to get smooth and stable IMFs. This approach results in improved component orthogonality and true reconstructability while remaining resistant to structural noise. The signal can be written as in (8).

$$x(t) = \sum_{i=1}^n \bar{c}_i(t) + r_n(t) \quad (8)$$

Where $\bar{c}_i(t)$ is the average of the IMFs extracted at each noisy step. CEEMDAN has been applied in various fields, such as stock index forecasting, biomedical signal processing, and climate analysis, and cryptocurrency price modeling [30]. When combined with LSTM, it separates out the high-frequency components (noise and micro-oscillations) to enable the training of LSTM to be concentrated on the signals, which are smoother and have more information. Therefore the CEEMDAN-LSTM network is especially fit to the aforementioned volatile and noisy financial series. To overcome EMD weaknesses, such as mode mixing, CEEMDAN is utilized to provide robust decomposition. The algorithm of the iterative ensemble approach to procure noise-robust IMFs from the input signal is presented in Algorithm 2.

Algorithm 2 Complete ensemble EMD with adaptive noise (CEEMDAN)

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1: Input: Signal  $x(t)$ , white noise  $w(t)$ , ensemble size  $M$ , noise level  $\varepsilon$ 
2: Output: Components  $\{c_1(t), c_2(t), \dots, c_n(t)\}$  and residual  $r_n(t)$ 
3: for  $m = 1$  to  $M$  do
4:    $x_m(t) \leftarrow x(t) + \varepsilon \cdot w_m(t)$ 
5:    $c_{1,m}(t) \leftarrow \text{EMD}(x_m(t))$  ▷ Apply EMD to noisy signal
6: end for
7:  $c_1(t) \leftarrow \frac{1}{M} \sum_{m=1}^M c_{1,m}(t)$  ▷ Ensemble average of first mode
8:  $r_1(t) \leftarrow x(t) - c_1(t)$ 
9: for  $i = 2$  to  $n$  do
10:  for  $m = 1$  to  $M$  do
11:     $r_{i-1,m}(t) \leftarrow r_{i-1}(t) + \varepsilon \cdot w_m(t)$ 
12:     $c_{i,m}(t) \leftarrow \text{EMD}(r_{i-1,m}(t))$ 
13:  end for
14:   $c_i(t) \leftarrow \frac{1}{M} \sum_{m=1}^M c_{i,m}(t)$  ▷ Ensemble average of  $i$ -th mode
15:   $r_i(t) \leftarrow r_{i-1}(t) - c_i(t)$ 
16: end for
17: return  $\{c_1(t), \dots, c_n(t)\}$  and  $r_n(t)$ 

```

CEEMDAN generate a series of ensembles with the addition of controlled white noise in the EMD decomposition operation. This helps to reduce the problem of mode mixing and produces smoother and

more interpretable IMFs. Each component obtained by the CEEMDAN decomposition represents independent frequency characteristics of the Bitcoin, which enhances the learning capacity of the LSTM and improves the robustness of prediction. The ensemble-based feature of CEEMDAN also leads to better signal reconstruction and generalization capabilities.

In both hybrid methods, IMF components (obtained from EMD or CEEMDAN) are normalized and fed into separate LSTM networks. All LSTMs learn the dynamics of their respective components. Additive predictions for all IMFs is then combined to get the final predicted Bitcoin price. This two-step process separates the short-term structures (fast IMFs) from the long-term structures (slow IMFs or the residuals), thus improving the accuracy of the model. In contrast, CNN architectures such as those used for series or image classification are not good at capturing long temporal dependencies and do not generalize well to very noisy one-dimensional signals. Likewise, classical approaches namely, ARIMA and GARCH are not able even to handle stationary series in such a non-stable and linear regime as the case of cryptocurrencies [31]–[33].

3.5. Grey relational analysis

In order to evaluate the importance of the factors on the target, or response variable (price of Bitcoin), the so-called GRA introduced in the grey systems theory was utilized [34]. This approach allows one to estimate the level of similarity of time series (including uncertainty, noise, and small amounts of statistical data). The reference series, corresponding to the Bitcoin price, is defined as (9).

$$X_0 = \{x_0(1), x_0(2), \dots, x_0(n)\} \quad (9)$$

The explanatory series is similarly defined in (10).

$$X_i = \{x_i(1), x_i(2), \dots, x_i(n)\} \quad (10)$$

The grey relational coefficient between $x_0(k)$ and $x_i(k)$ is expressed by (11).

$$\xi_i(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \zeta \cdot \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \zeta \cdot \max_i \max_k |x_0(k) - x_i(k)|} \quad (11)$$

Here, $\zeta \in [0, 1]$ denotes the distinction coefficient, which is usually set to 0.5. The overall grey relational degree between X_0 and X_i is then computed using (12).

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \quad (12)$$

The closer γ_i is to 1, the higher the structural similarity between the explanatory variable X_i and the target series X_0 . This method is well adapted to non-stationary financial time-series such as those examined in [35] and to the problem of variable selection prior to modeling.

3.6. Evaluation criteria

In order to assess the forecasting accuracy of the models for the time series of the Bitcoin price, two typical criteria are employed: the RMSE and the mean absolute error (MAE). These measurements indicate the deviation between predicted and actual values. The RMSE metric is defined in (13).

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (13)$$

It represents the square root of the mean squared error and expresses the average prediction error in the same unit as the data. The MAE metric is defined in (14).

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (14)$$

MAE measures the average absolute prediction error and is generally more robust to outliers since it does not excessively penalize large deviations.

4. DATA COLLECTION AND SOURCES

The purpose of this study is to forecast the path of the Bitcoin price by including, beyond its past behavior, a number of macro-financial variables that can potentially affect its movement in the short/medium term. Because the cryptocurrency market is diverse, as control variables were selected a series of indicators standing for the global economy situation, the U.S. monetary policy, the capital flow towards safe-haven assets, and the dollar dynamics. Data were collected over a ten-year period from September 2014 to September 2024, with a daily frequency and standardized prior to including to models.

4.1. Crude oil price West Texas Intermediate

The barometer of global economic activity that is the oil price was chosen as the first explanatory variable. The demand for oil tends to rise during an economic expansion, and fall when the economy is in a recession or is slowing down [36]. Additionally, the volatility of oil might also affect the expectations of investors regarding inflation and monetary policy, and then speculative assets such as Bitcoin [37].

4.2. Gold price (XAU/USD)

Gold has long been considered a refuge in insecure times such as geopolitical turmoil or financial crises [38]. Its dynamics typically embody the anticipation of systemic risk and inflation. When the market stresses, investors will reduce their exposures to risky assets, and the risk aversion will push up the demand for gold; the latter could drive capital flight out of cryptocurrencies into safer assets [39]. Therefore, the behaviour of gold's price is a good indicator of the general risk aversion.

4.3. 2-year United States treasury bond rates

The 2-year Treasury bond yield is strongly related to the market's beliefs about the monetary policy of the Fed [40]. So a low rate implies an accommodative monetary stance (lower key rates and expanding balance sheet), and is good for speculative assets and the stock market; whereas a high rate speaks of a monetary tightening, which means less liquidity and more stress on risky assets. In this, the 2Y rate is a key driver of risk appetite perception and of cross-asset arbitrage [41].

4.4. United States dollar index

The dollar index (DXY) is a measure of the value of the United States dollar (U.S. dollar) relative to a basket of six foreign currencies (euro, Japanese yen, pound sterling, Canadian dollar, Swedish krona, and Swiss franc). The dollar is a reserve currency for the world and is frequently seen as a safe haven. A strong U.S. dollar typically means a downturn in risk appetite or increased global interest rate tightening, while a weak U.S. dollar can mean a positive environment for non-U.S. dollar assets [42]. Bitcoin, at times touted as a currency-inflation hedge, frequently experiences a negative dynamic with the DXY [43].

5. RESULTS AND DISCUSSION

5.1. Results

Figure 2 shows the output of the GRA for the different explanatory variables. Each of the lines is indexed to different time intervals: daily (1d), daily excluding weekends (1d b), weekly (1w), monthly (1m), and quarterly (1q) series. From this visualization, it is possible to evaluate not only the structure of relationship on the basis of all variables considered, and their relation to the price of Bitcoin, but also the role of the sampling frequency on the capacity to explain it. The comparison shows that the daily data generally have the highest values of GRA. Crude oil price, Gold price, US 2Y interest rate, and U.S. dollar index have a close GR relationship with Bitcoin, especially in high frequency. These findings indicate that the fluctuations of these indicators are highly correlated to daily changes of Bitcoin trading.

Accordingly, the model was designed and trained using only the daily data, as it is the scale over which the information is most relevant according to GRA. This option can capture short-term information more precisely and avoid information loss caused by temporal aggregation. It also mirrors the short-term horizon upon which crypto markets operate, namely their acute sensitivity to economic data and geopolitical shocks. Figures 3 and 4 show the extracted IMF components by the EMD method and the CEEMDAN, respectively. It is noticed that the separation of frequency presented is finer and less noisy in CEEMDAN, resulting in better-usable signals for the sequential LSTM training. Especially, it can produce a better separation of high frequency components, at the same time, an accurate trend is more distinct.

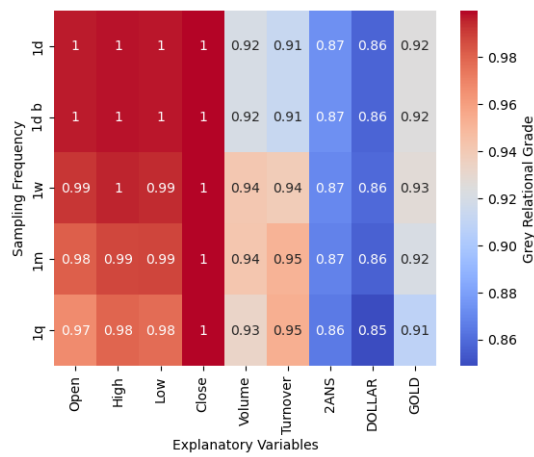


Figure 2. The results of GRA on predictors

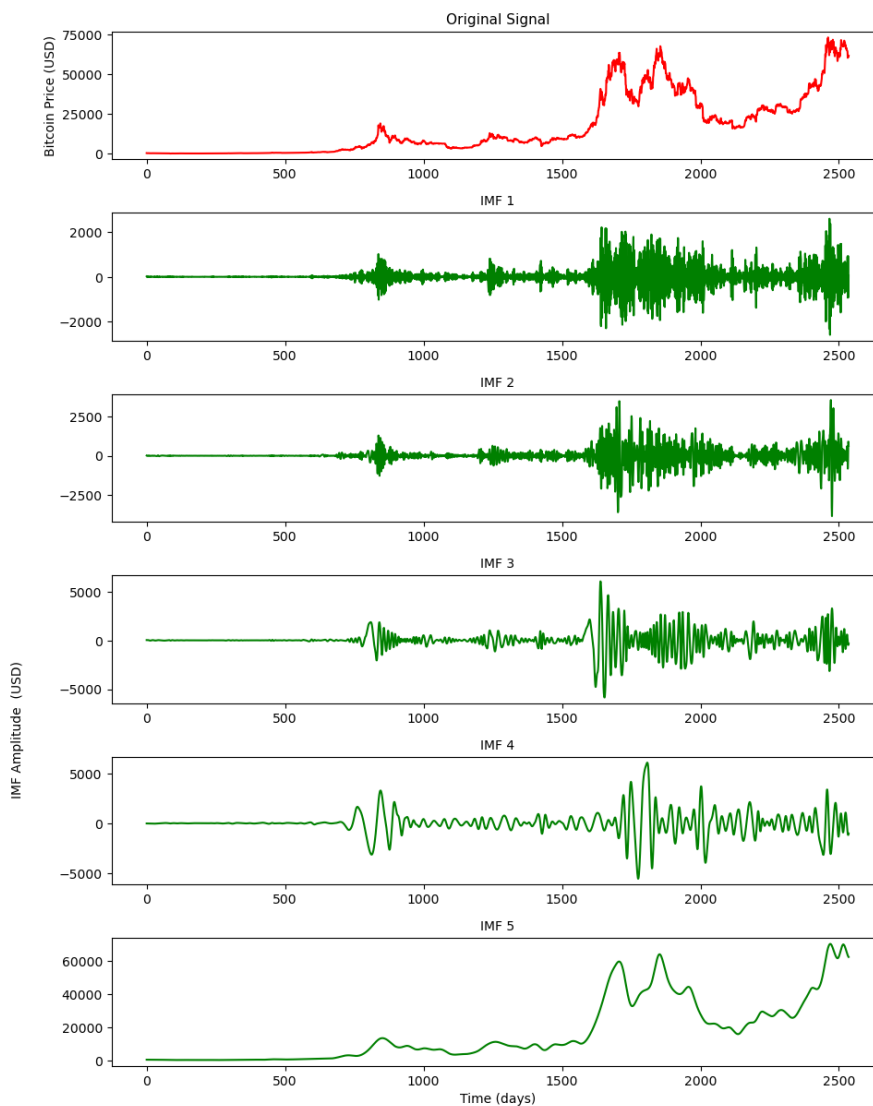


Figure 3. The IMFs decomposed by EMD

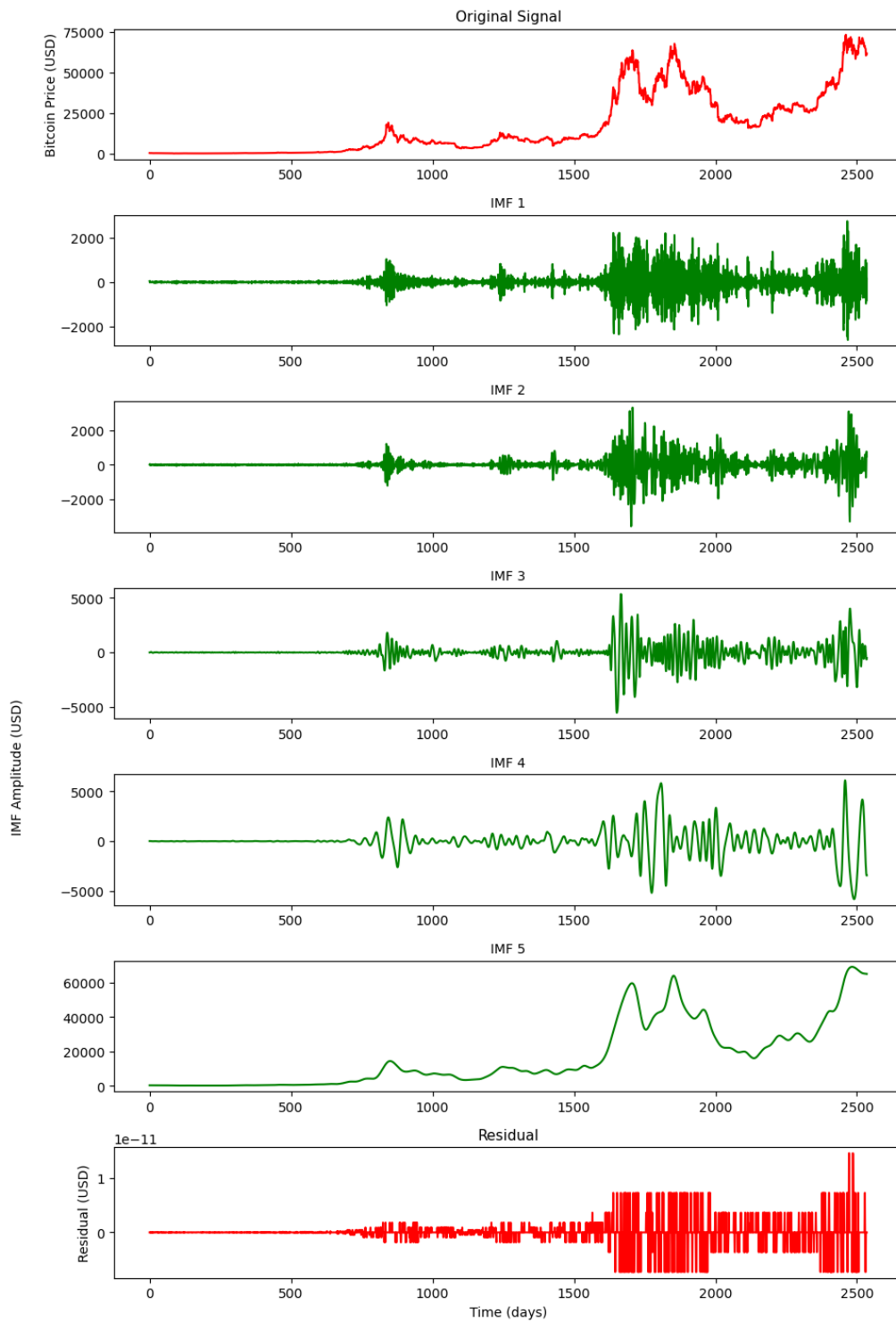


Figure 4. The IMFs decomposed by CEEMDAN

The performances are summarized quantitatively in Table 2. The proposed baseline LSTM model provides an MAE of 169.516 and an RMSE of 256.225. Tolerable performances can be achieved by including EMD decomposition (MAE =168.785; RMSE =256.042). Last, the combination of CEEMDAN yields the best performance (MAE =167.837; RMSE =255.673) overall.

Table 2. Performance comparison between LSTM, EMD-LSTM, and CEEMDAN-LSTM models

Metric	LSTM	EMD-LSTM	CEEMDAN-LSTM
MAE	169.516	168.785	167.837
RMSE	256.225	256.042	255.673

Visual predictions are visualized in Figures 5 to 7. Figure 5 shows the forecast of the LSTM model, being capable to recognize the global trend, it misses some quick reversals. Figure 6 implemented with the EMD-LSTM model possesses more sensitivity to local change, which is an immediate consequence of the IMF preprocessing. Figure 7 shows that CEEMDAN-LSTM presents the best accuracy both on up and down trend is obtained with least error than all other results. The learning curves development indicates that the CEEMDAN decomposition is capable of providing the LSTM model more solid pattern to grasp the, thus mitigating the influence of abnormal fluctuations of the Bitcoin price.

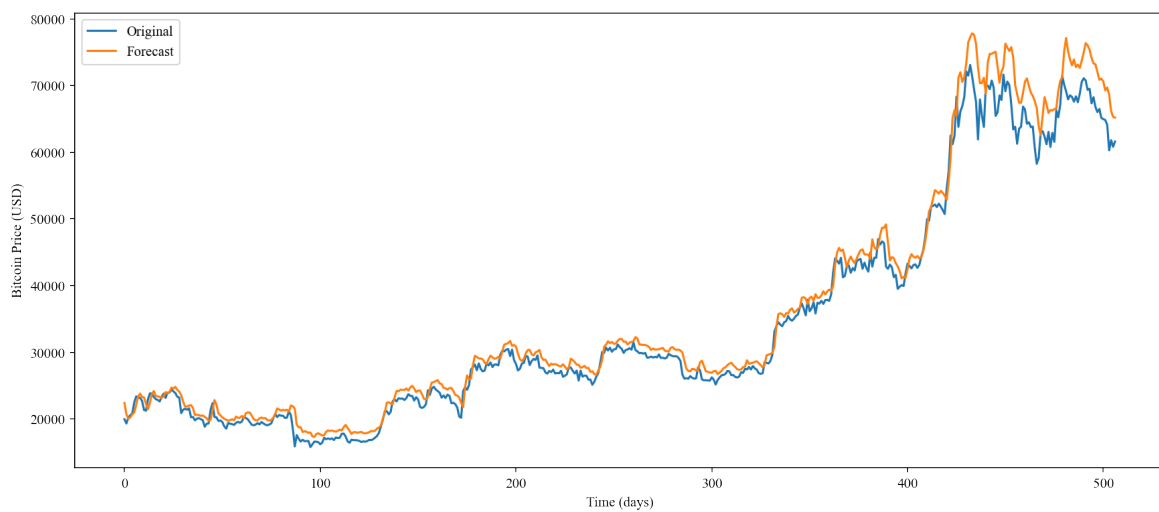


Figure 5. The forecasting results based on LSTM

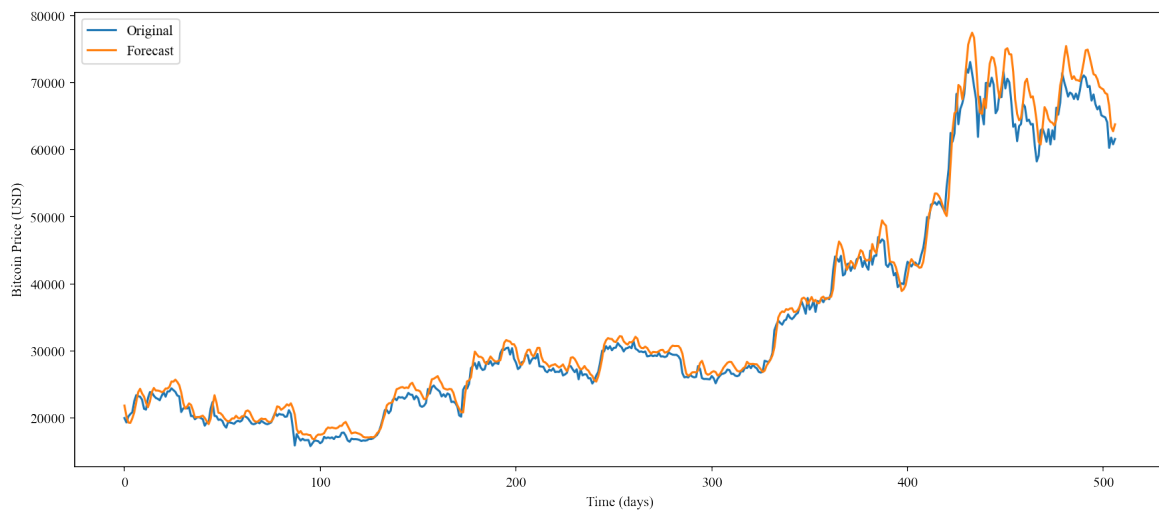


Figure 6. The forecasting results based on EMD-LSTM

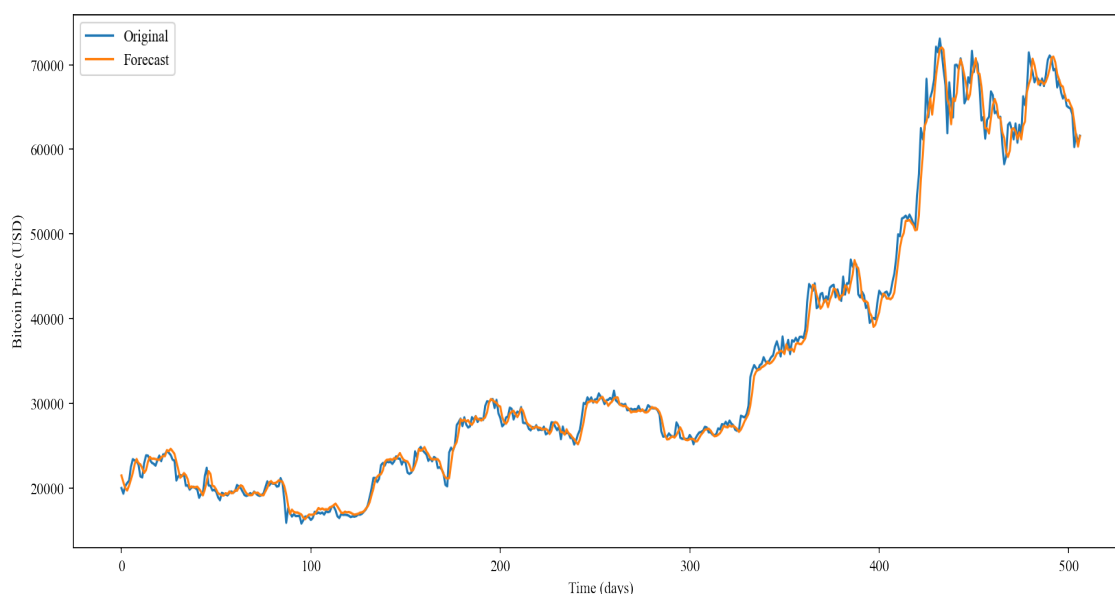


Figure 7. The forecasting results based on CEEMDAN-LSTM

5.2. Discussion

The results also align with other recent advancements made for predictive modeling of cryptocurrency market. A comparison can be made with the work of Livieris [44], which presents a CNN-LSTM model over Bitcoin. Even with their architecture being more complex and deeper (multiple convolution layers), the CEEMDAN-LSTM model shows higher prediction accuracy than theirs.

This performance gap is quite striking due to the architectural simplicity of our model. The enhancement is mostly due to the CEEMDAN-based pre-processing of the LSTM, which presents the LSTM with more stable and informative subseries. Secondly, use a multivariate approach with exogenous macro-financial factors chosen by GRA, while theirs is a univariate one based on the historical information of Bitcoin. This suggests that even the structure and relevance of the input features can be just as important, if not more important, than the choice of our model architecture.

This view is supported by recent work in the field. For example, the CNN-GRU hybrid model made by Chauhan *et al.* [18], used for long-term Bitcoin prediction, although it is constructed by using a deeper and more complex structure, it yields lower predictive accuracy compared to our model. In the same vein, comparative research investigating the traditional models realized by Qureshi *et al.* [19], such as ARIMA, MLP, and ELM, including their hybrid variants, have had limited success in capturing the extremely non-linear nature of cryptocurrency markets compared to the proposed approach.

In sum, these comparisons indicate that integrating adaptive signal decomposition with deep sequence modeling in the multivariate fashion is a strong approach to learn high-level representations. Rather than exclusively using deep architectures, the necessity of data transformation, variable selection, and signal conditioning is emphasized as the main sources of accurate and robust forecasting models of highly complex financial environment, like markets for cryptocurrencies. Furthermore, the approach is also computationally less expensive than others, rendering it useful for real time or resource constrained prediction scenarios, with little to no trade-off in accuracy.

6. CONCLUSION

Multiple sampling frequencies were evaluated during the feature-selection stage (GRA) and ultimately trained the forecasting models on daily data, which proved most informative. This modular and interpretable model provides a robust basis for modeling nonlinear financial series. Several avenues can be explored to strengthen this architecture. First, integrating sentiment indicators from social media, forums, or surveys (such as the consumer confidence index) would make it possible to model behavioral dynamics. Second, including technical analysis indicators (such as RSI, MACD, and bollinger bands) could enrich

the sequential representation with signals from the market itself. Furthermore, alternative decomposition techniques (variational mode decomposition (VMD) and singular spectrum analysis (SSA)), or attention-based architectures (transformers and attention-LSTM), would offer promising avenues for improving the model's responsiveness to regime changes. Extending the model to multivariate, multi-horizon (forecasting at different timescales simultaneously) or multimodal (incorporating text, audio, or image) frameworks could also advance the state of the art in financial prediction. In summary, this study highlights the crucial importance of structured signal preprocessing and economically consistent variable selection as key factors in the successful predictive modeling of complex markets such as cryptocurrencies.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ayoub Aarabi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓
Maryem Ait Moulay	✓			✓	✓	✓	✓	✓	✓	✓	✓			✓
Issam Bouganssa		✓	✓	✓	✓	✓				✓	✓	✓		
Abdelali Lasfar	✓	✓		✓						✓	✓	✓	✓	

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal Analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project Administration

Fu : Funding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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BIOGRAPHIES OF AUTHORS






Ayoub Aarabi    holds an engineering degree from Mohammadia School of Engineering in Rabat, Morocco. He also earned a master's degree in Applied Mathematics, with a specialization in Quantitative Finance, from Paris-Saclay University in Paris, France. He is currently a portfolio manager and a Ph.D. candidate at the LASTIMI Laboratory, Mohammed V University of Rabat, pursuing research in the field of machine learning applied to finance. His interests include quantitative portfolio management and financial machine learning. He can be contacted at: ayoub.arb@gmail.com.






Maryem Ait Moulay    is a Ph.D. student at the Laboratory Systems Analysis, Information Processing, and Industrial Management, Mohammadia School of Engineering (EMI), Mohammed V University of Rabat, Morocco. Passionate about artificial intelligence. Her focus is on exploring innovative applications in artificial intelligence, computer vision, and information processing. She can be contacted at email: maryem_aitmoulay2@um5.ac.ma.



Issam Bouganssa    is a professor at Mohammed V University in Rabat since 2019, active in embedded systems and industrial computing. Ph.D. in science and technology for engineers specializing in automation and embedded systems at the LASTIMI Laboratory, Mohammed V University of Rabat. He can be contacted at email: issam.bouganssa@gmail.com.



Abdelali Lasfar    is a professor of Higher Education at Mohammed V Agdal University, Salé Higher School of Technology, Morocco. His research focuses on compression methods, indexing by image content and image at the LASTIMI Laboratory. He can be contacted at email: abdelali.lasfar@est.um5.ac.ma.