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Cycle Forecasting in Financial Markets with LSTM and Discrete Fourier Transform

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Abstract – The study of cyclicality in capital markets is important for forecasting the prices of traded financial instruments and improving investment strategies. Cycles can be influenced by various factors – economic conditions, business activity, political events, and even market participants' psychology – making their analysis challenging. This paper presents a study aimed at detecting cyclicality in time series using a hybrid model. Recurrent neural networks of the Long Short-Term Memory (LSTM) type are combined with Discrete Fourier Transform for frequency component analysis. The model is trained on simulated market data containing clearly defined sinusoidal cycles and stochastic noise to assess the LSTM network's ability to capture the period, frequency, and amplitude of market fluctuations. Experiments were conducted with varying numbers of hidden neurons in the LSTM layer, and the results show that increasing architectural complexity improves amplitude prediction, while frequency and period are captured with high accuracy across all configurations.

Keywords – financial markets, cyclicality, LSTM, spectral analysis, Fourier transforms.

1. Introduction

Forecasting the cyclicality of financial markets is of paramount importance in today's dynamic world, where an increasing number of individuals invest in stocks and other financial instruments. It enables stakeholders to better understand and anticipate market behavior. Recognizing market cycles helps investors manage their portfolios more effectively, increase returns, and minimize risk. Moreover, financial markets often reflect future economic changes in advance. Early detection of recession signals allows for loss minimization through hedging or portfolio rebalancing.

The cyclicality of capital markets depends on numerous factors. A wide range of circumstances and cycles – economic, political, monetary, behavioral, and others – simultaneously and variably influence the movement of financial instrument prices. Some cycles are short-term, lasting days or weeks, while others are long-term, spanning years or even decades. Additionally, financial data is characterized by a high level of noise generated by random, irrational, or insignificant events. The advancement of computational technologies and artificial intelligence in recent years has provided a foundation for conducting more complex and resource-intensive analyses, such as wavelet transformations, Monte Carlo simulations, artificial neural networks (ANNs), and others. New models inspired by physics, biology, and engineering are being developed. However, no universal tool, algorithm, or technology can capture all aspects of cyclicality. Some models perform better during periods of growth, others during crises; some are more effective at capturing short-term fluctuations, while others are better suited for long-term trends; some are sensitive to noise, while others are not, and so on. This drives the development and investigation of complex models that combine different methods and algorithms and demonstrate adaptability to varying conditions.

This paper discusses several fundamental methods for analyzing the cyclicality of financial markets and approaches for time series analysis. It also proposes and investigates a hybrid model based on a recurrent neural network with Long Short-Term Memory (LSTM) and spectral analysis using Fourier

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transforms. The study addresses the following research questions:

- To what extent can LSTM networks trained on noisy, simulated cyclical data accurately capture the period and frequency of the underlying cycles?
- How does the number of hidden neurons in the LSTM architecture affect the prediction of the amplitude of cyclical patterns?
- Can the integration of DFT with LSTM improve the model's ability to detect frequency components that may remain hidden in the residual error of time series forecasts?

By addressing these questions, the study aims to evaluate the effectiveness and limitations of neural-based hybrid models in identifying cyclical structures within financial time series, contributing to the broader field of AI-assisted financial forecasting

2. Cyclicality in Financial Markets and Standard Tools for Its Analysis

The complex nonlinear, chaotic, and stochastic behavior of financial markets requires a rich set of tools for their analysis. A wide variety of instruments and technologies are used to study cyclicality, ranging from empirical methods to machine learning and ANNs.

2.1. Technical Indicators

Some of the most popular technical indicators used for analyzing and forecasting financial markets – and in particular their cyclicality – are moving averages. The Simple Moving Average (SMA) is calculated using the following formula:

$$SMA = \frac{1}{n}\sum_{i=1}^{n} P_i, \quad (1)$$

where n is the number of observations (periods), and P_i are the asset values for each of those periods. The SMA determines the average value of the asset over a specific time period and is commonly used to smooth out price fluctuations and detect cycles or simply identify trend changes [1–4].

On the other hand, the Exponential Moving Average (EMA) assigns more weight to recent values compared to older data. This makes it more sensitive to recent price changes than the SMA. For the current period t, the EMA is represented as:

$$EMA_t = \alpha P_t + (1-\alpha)EMA_{t-1}, \quad (2)$$

where EMA_t and EMA_{t-1} are the exponential moving averages for the current and previous periods, respectively. The smoothing coefficient, which generally takes the form:

$$\alpha = \frac{2}{n+1} \quad (3)$$

is designed to control the weighting of recent data (see Figure 1).

In their work, Karasu and Altan use exponential moving averages to generate features required for a crude oil price forecasting model that incorporates LSTM [5]. On the other hand, Lucas and Zhang utilize an extension of the Exponentially Weighted Moving Average (EWMA) and develop a methodology for modeling volatility using a recursive updating scheme [6].

The Relative Strength Index (RSI) is used to analyze the momentum of price movements. It helps identify whether an asset is overbought or oversold and can be used to detect the beginning or end of a cycle in the behavior of a financial or commodity asset. RSI is calculated based on the ratio between average gains (AG) and average losses (AL) over a given period:

$$RSI = 100 - \frac{100}{1+\frac{AG}{AL}}, \quad (4)$$

where:

$$AG = \frac{1}{n}\sum_{i=1}^{n} AG_i\,, AL = \frac{1}{n}\sum_{i=1}^{n} AL_i. \quad (5)$$

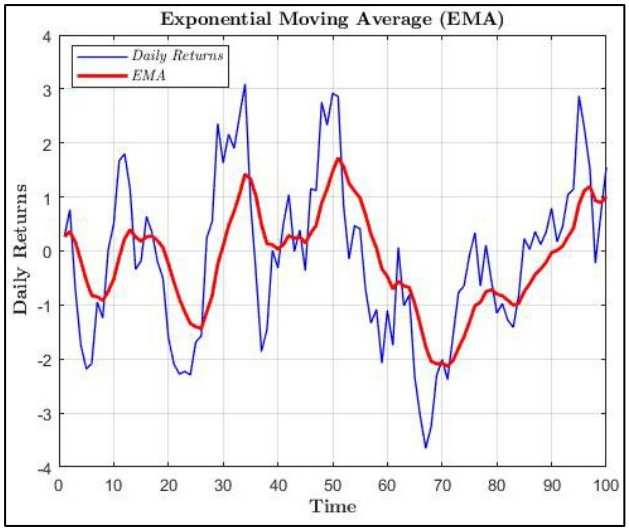


Figure 1. Example of an Exponential Moving Average for the daily return of a given asset (Matlab v.2018a).

RSI is one of the most commonly used indicators in technical analysis because it provides clear signals for overbought or oversold conditions, helping traders make informed decisions about market entry or exit. Examples of RSI applications can be found in [7–10].

Another popular technical tool that measures the momentum of price movements and is used to detect overbought or oversold market conditions is the Stochastic Oscillator [11–14]. It is based on the assumption that, in an uptrend, prices tend to close near the high of the price range for a given period, while in a downtrend, they tend to close near the low.

The Stochastic Oscillator consists of two lines:

- $\%K$ line (fast line): the main line that measures the current price relative to the price range.
- $\%D$ line (slow smoothed line): used as a signal line for $\%K$.

The mathematical model of the $\%K$ line expresses the position of the current price as a percentage of the price range over the past n periods:

$$\%K = 100 \times \frac{C - L_n}{H_n - L_n}, \quad (6)$$

where:

- C is the current closing price;
- L_n is the lowest price over the past n periods;
- H_n is the highest price over the past n periods;
- n is typically 14 but may vary depending on the analyst's preferences.

The formula for the $\%D$ line is based on the measured values of $\%K$ and is simply defined as a simple moving average of $\%K$ over the last m periods:

$$\%D = \frac{\sum \%K}{m}. \quad (7)$$

The following thresholds are commonly used when interpreting the Stochastic Oscillator to identify overbought or oversold conditions:

- Overbought conditions: When the Stochastic Oscillator (especially $\%K$) is above 80, the market is considered overbought, which may indicate a potential reversal or downward correction.
- Oversold conditions: When the Stochastic Oscillator value is below 20, the market is considered oversold, which may indicate a potential upward reversal.

Based on this, the following trading signals are formulated:

- Buy signal: When $\%K$ crosses above $\%D$ and both lines are in the oversold zone (below 20).
- Sell signal: When $\%K$ crosses below $\%D$ and both lines are in the overbought zone (above 80).

2.2. Time-Based Analysis of Market Cyclicality

Time-based analysis of market cyclicality is the process of examining time series data to identify and measure recurring patterns or cycles in market movements. The goal is to understand how and when certain market trends emerge that follow predictable patterns, including upward and downward movements, periods of volatility, and long-term trends. This analysis supports improved forecasting and decision-making in portfolio management, trading, and financial planning [15–18].

The main components of time-based cycle analysis include:

1. Identifying the cycle length: The analysis focuses on determining the periodicity of different cycles – whether they are short-term, medium-term, or long-term. Short-term cycles may span hours or days, medium-term cycles span months, and long-term cycles can last for years.
2. Estimating the cycle amplitude: Amplitude describes the price fluctuations between the peaks and troughs of a cycle and provides insight into the extent of variation, which is useful for risk assessment.
3. Analyzing the cycle phase: The cycle phase indicates whether the market is in an upward or downward trend. This is useful for predicting turning points where one trend ends and another begins, as well as for identifying support and resistance zones in market prices.
4. Identifying seasonal and temporal anomalies: Seasonal patterns – such as increased activity at the end of the year or summer downturns – are often revealed in time-based analysis and are significant for financial planning and forecasting.

A commonly used approach in cyclicality analysis is fractal time analysis of the market, where financial data is examined through the lens of fractal geometry [19–22]. This approach is based on the notion that market price movements are not purely linear and often exhibit recurring, self-similar structures across different time scales. Unlike traditional analysis, which assumes market movements are "smooth" and linear, fractal analysis is grounded in the understanding that they are often chaotic and irregular. Instead of following perfect cycles, markets move in complex patterns that nevertheless repeat with a certain degree of regularity.

Fractal analysis employs various mathematical methods and models to uncover the cyclicality of financial markets. One such model is the fractal dimension – a mathematical measure that describes how “complex” the structure of a market time series is [23,24]. Figure 2 presents a visualization demonstrating how specific segments of a time series can be analyzed through the prism of fractal geometry in order to identify self-similar structures in market movements.

One of the commonly used methods for measuring fractal dimension is the Correlation Dimension method.

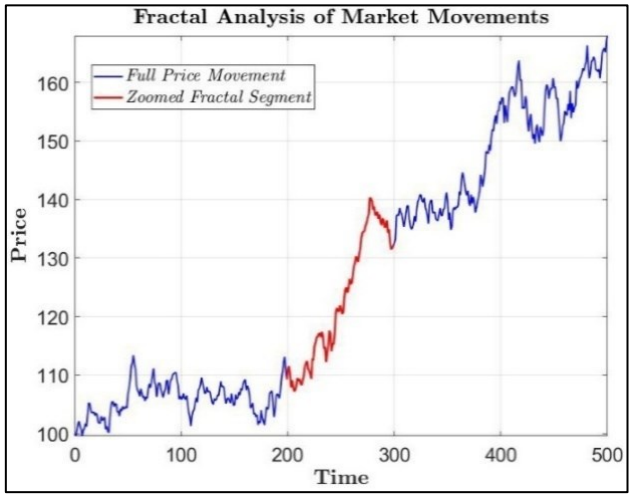


Figure 2. Example of fractality in market movement (Matlab v.2018a).

On the other hand, the Hurst exponent H is a fundamental tool for analyzing market cyclicality and predictability through fractals, as it measures the degree of long-term dependence in the data. It is calculated using the formula:

$$H = \lim_{n\to\infty} \frac{\log(R/S)}{\log(n)}, \quad (8)$$

where R is the range of deviations in values over a period n, and S is the standard deviation.

The following criteria are used when interpreting the Hurst exponent:

- If $H = 0.5$, the market behaves randomly and lacks predictability.
- If $H > 0.5$, the data exhibits a trend (positive autocorrelation), suggesting that previous movements are likely to continue in the same direction.
- If $H < 0.5$, the market shows mean-reverting behavior (negative autocorrelation), meaning frequent reversals in movement are more likely.

Examples of the application of the Hurst exponent H in the financial world can be found in studies such as [25–28].

In the 1930s, a concept in technical analysis became popular that describes recurring market patterns through a series of waves. This is the Elliott Wave Theory, which proposes that market movements reflect the collective psychology of investors and manifest in specific cycles and wave structures. According to Elliott, these patterns are fractal in nature and appear across multiple time scales.

The key principles of the Elliott Wave Theory include (Figure 3):

- The basic wave structure: According to the theory, market movements consist of impulse waves (moving in the direction of the main trend) and corrective waves (moving in the opposite direction). Impulse waves contain five sub-waves and follow the direction of the trend. Corrective waves consist of three sub-waves and correct the impulse movement, typically moving against the main trend.
- Impulse structure (5-3 wave pattern): A full cycle consists of 5 impulse waves (1, 2, 3, 4, and 5), followed by 3 corrective waves (A, B, and C). This means a complete market cycle comprises 8 waves – 5 upward (in the direction of the trend) and 3 corrective (in the opposite direction).

According to the theory, Elliott waves are fractal, meaning that each wave can be broken down into smaller waves that also follow the same 5-3 structure. This enables the theory to be applied across different time scales, from minute charts to yearly time frames. Elliott waves can be used to analyze cyclicality by identifying the sequence of waves that reflect recurring market behaviors. According to Elliott, when the market is trending, it passes through predictable phases of growth and correction, which are part of the natural market cycles.

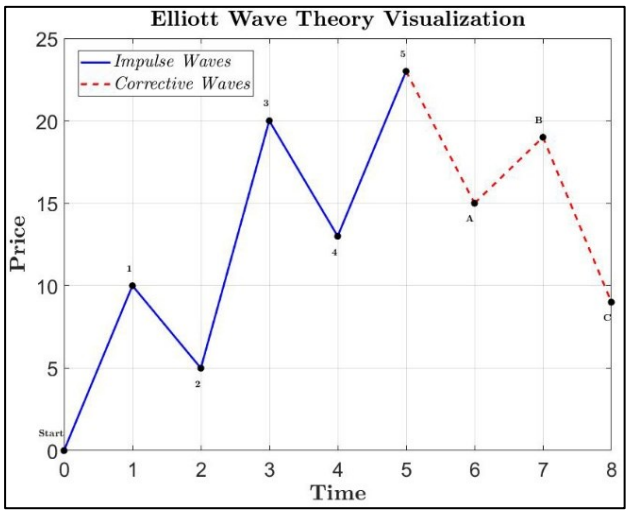


Figure 3. Fundamental principles of Elliott Wave Theory (Matlab v.2018a).

In fractal analysis, the Fractal Wave Theory is also used. It builds upon the concept of Elliott Wave Theory and is based on the idea that market movements consist of multiple waves of varying duration, appearing across different time scales and exhibiting similar structures. This theory is employed to identify patterns and cycles at different temporal levels [29–32].

On the other hand, Multifractal Time Analysis uses multifractals to examine the markets. It allows for the detection of different fractal dimensions across various time intervals. This method provides a more detailed understanding of market complexity and the

ability to study different cycles at different time scales [33–36].

A powerful technique within time-based analysis of market cyclicality is Fibonacci time extensions (Fibonacci extension levels). These utilize the Fibonacci sequence to forecast time points at which significant market changes – such as trend reversals or state transitions – are likely to occur [37–40]. Unlike traditional Fibonacci levels, which focus on price ranges, Fibonacci time extensions consider the temporal component of cyclicality and offer a method for analyzing the timing of trend reversals and major price movements. The idea is based on the Fibonacci sequence (1, 1, 2, 3, 5, 8, 13, 21, ...), where each number is the sum of the two preceding ones. This sequence produces ratios such as 0.618 (61.8%), 1.618 (161.8%), and 2.618 (261.8%), which are widely used in technical analysis. In time extensions, a key market cycle is typically identified (e.g., a move from point A to point B), and then Fibonacci time ratios are applied to determine when significant market shifts are likely to occur.

2.3. Statistical Models for Analyzing Market Cyclicality

Statistical models for analyzing the cyclicality of financial markets are methods that utilize historical data to forecast future movements. These models focus on identifying recurring patterns and cycles. Their goal is to uncover hidden cyclical structures in the data using various statistical and mathematical techniques.

One commonly used approach in this context is the $ARIMA$ model. This model combines three core components:

- AR (Autoregressive): The autoregressive component uses the relationship between the current value and previous values in the time series.
- I (Integrated): The integration component removes trends in the data through differencing.
- MA (Moving Average): The moving average component is based on the relationship between the current value and errors from previous forecasts.

The $ARIMA$ model is denoted as $ARIMA(p, d, q)$, where p is the order of the autoregression, d is the degree of differencing, and q is the order of the moving average. It is defined by the following equation:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots \theta_q \varepsilon_{t-q}, \quad (9)$$

where:

- Y_t is the value of the time series at time t;
- c is a constant;
- ϕ_i are the autoregressive coefficients;
- ε_t is the random error (noise) at time t;
- θ_i are the moving average coefficients.

In study [41], the $ARIMA$ model approach is used to forecast the stock prices of pharmaceutical companies, while in [42] it is applied to predict financial anomalies and trends in corporate financial development, helping companies manage risk and make informed investment decisions.

A widely used extension of $ARIMA$ is the $SARIMA$ model, which incorporates seasonal components and is especially useful for analyzing cyclicality in market data with pronounced seasonality [43–46]. This model adds seasonal parameters to $ARIMA$ using the structure $SARIMA(p, d, q)\ (P, D, Q)_s$, where P, D, Q are the seasonal counterparts of the autoregressive, differencing, and moving average components, and s is the seasonal period (e.g., $s = 12$ for yearly seasonality in monthly data).

The $SARIMA$ formula incorporates both seasonal AR and MA components, as follows:

$$Y_t = c + \phi(B) Y_{t-1} + \Phi(B^s) Y_{t-s} + \varepsilon_t + \theta(B) \varepsilon_{t-1} + \Theta(B^s) \varepsilon_{t-s}, \quad (10)$$

where:

- B is the lag operator for the time series;
- $\phi(B)$ is the autoregressive operator;
- $\Phi(B^s)$ is the seasonal autoregressive operator;
- $\theta(B)$ is the moving average operator;
- $\Theta(B^s)$ is the seasonal moving average operator.

Examples of $SARIMA$ applications in financial event analysis can be found in the works of [42, 44–46].

Another approach within the framework of statistical models for analyzing market cyclicality is the Hodrick–Prescott Filter (HP Filter), which decomposes time series into trend and cyclical components (Figure 4). It is particularly popular in macroeconomic analysis and is useful for isolating long-term trends from short-term cycles in the data. The HP filter aims to minimize the following expression:

$$\min_{T_t} A = \min_{T_t} \sum_{t=1}^{T} (Y_t - T_t)^2 + \lambda \sum_{t=2}^{T-1} [(T_{t+1} - T_t) - (T_t - T_{t-1})]^2, \quad (11)$$

where:

- Y_t is the value of the time series at period t;
- T_t is the long-term trend component of the time series;

- λ is a parameter that controls the degree of smoothing of the trend (higher values of λ result in a smoother trend).

The first term, $(Y_t - T_t)^2$, minimizes the deviation between the original data and the trend component to keep the trend close to the actual data. The second term controls the smoothness of the trend, ensuring it is stable and gradual.

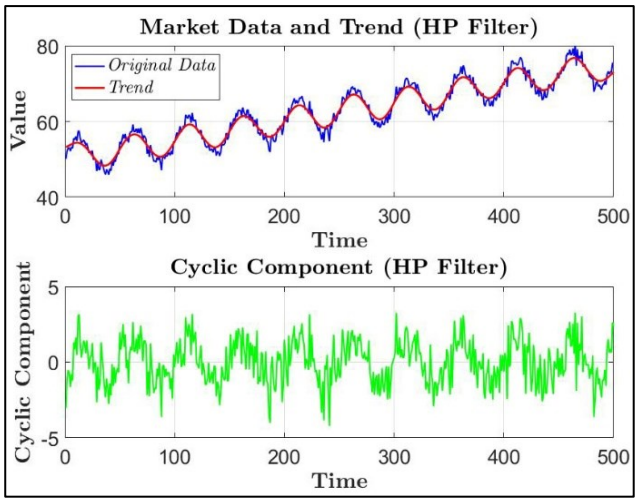


Figure 4. Hodrick–Prescott filter for decomposing a time series into trend and cyclical components (Matlab v.2018a).

In their work, Ilyas et al. use a modified Hodrick–Prescott filter to smooth historical stock price data by removing the cyclical component from the time series [47]. Quande et al. demonstrate how novel filter-based modeling with Hodrick–Prescott (HP) filter, that can identify repeated up and down structural features around a certain carbon price, negotiates the obstacle of the parallel–series hybridization concerning the linear and the nonlinear model [48]. Other notable applications of the HP Filter are presented in [49–52].

2.4. Cyclical Indices and Indicators

Several economic and financial indices can also be used to identify market cyclicality. For example, business activity indices, the Purchasing Managers' Index (PMI), employment data, and inflation figures are key economic indicators that provide insight into the state of the economy and are used to assess economic cycles. These indicators help to determine the current phase of the economy (expansion, slowdown, or recession) and to forecast future trends [53–56].

Business activity indices reflect the overall level of activity in various sectors of the economy. They are based on surveys of company managers who assess conditions in their sector, such as order volume, production, new orders, employment, etc. When business activity indices show high values, it indicates that the economy is in a period of expansion; conversely, a decline in these indices may signal an upcoming downturn or recession.

On the other hand, the PMI is a key indicator of economic activity in the manufacturing sector, based on surveys of purchasing managers. The index includes components such as new orders, production level, supplier deliveries, inventories, and employment [57–60].

A PMI value above 50 indicates growth in the manufacturing sector and signals economic development, while values below 50 suggest contraction, potentially foreshadowing a recession. PMI is often considered a leading indicator, as it tends to react faster to changes in the economy than some other measures.

Employment indicators are also widely used, including unemployment rates, changes in employment levels, and average wages. These metrics are critical for assessing economic health. Higher employment levels reflect a more active economy, whereas rising unemployment may indicate an economic slowdown.

Another major indicator used to assess the market is the inflation rate, which measures the pace of price increases for goods and services in the economy. Indicators such as the Consumer Price Index (CPI) and the Producer Price Index (PPI) are used to track inflationary pressures. Moderate inflation often accompanies economic growth, while excessive inflation may lead to an overheated economy and necessitate cooling measures (e.g., interest rate hikes). Conversely, deflation or very low inflation can signal economic weakness and low consumer demand.

When combined, these indicators offer a comprehensive picture of the current economic condition and enhance our understanding of its cyclicality:

- Expansion phase: High PMI values, rising employment, and moderate inflation are typical of periods of economic growth.
- Slowdown phase: If business activity indices and PMI begin to decline, and unemployment slightly rises, it may indicate an upcoming slowdown.
- Recession: A sharp drop in PMI and business activity indices, high unemployment, and low inflation (or deflation) often accompany a recession.
- Recovery: When PMI and business activity indices start to rise again and unemployment begins to decline, it signals the beginning of economic recovery.

2.5. Seasonality and Calendar Effects

Seasonal and calendar effects are specific time-based patterns in financial markets that exhibit cyclically recurring behavior during certain times of the year, month, or week. These effects are based on historical observations and can be used to forecast likely market movements.

Seasonal analysis focuses on trends during particular periods of the year when markets demonstrate predictable behavior [61–64]. One example is the so-called December effect (or Santa Claus rally), during which stock markets tend to rise in the final days of December and the first days of January. Another example is the summer trading slowdown ("Sell in May and go away"), where trading activity often declines during the summer months.

Seasonal effects can be analyzed using seasonal $ARIMA$ ($SARIMA$) models or seasonal decomposition, which views a time series as a combination of three components: trend (T_t), seasonality (S_t), and random noise (R_t):

$$Y_t = T_t + S_t + R_t, \quad (12)$$

where Y_t is the observed value of the time series at time t, and the seasonal component S_t is calculated based on recurring patterns in the data. It reveals how seasonal effects influence market cyclicality.

On the other hand, calendar anomalies refer to specific cyclical behaviors associated with certain days of the week or month [65–68]. An example is the Monday effect, where markets often underperform, or the Friday effect, which may be accompanied by increased volatility (Figure 6). Such effects are often attributed to specific trading practices or psychological factors.

To analyze whether certain days of the week influence returns, one can construct a regression model with dummy variables. For example:

$$Y_t = \alpha + \beta_1 D_{Mon} + \beta_2 D_{Tue} + \beta_3 D_{Wed} + \beta_4 D_{Thu} + \beta_5 D_{Fri} + \varepsilon_t, \quad (13)$$

where:

- Y_t is the return of the asset on day t;
- $D_{Mon}, D_{Tue} \ldots, D_{Fri}$ are dummy variables equal to 1 if the day is the corresponding weekday, and 0 otherwise;
- $\beta_1, \beta_2, \ldots, \beta_5$ are coefficients indicating the effect of each weekday on returns;
- ε_t is the random error.

The constant coefficient α in equation (13) holds particular significance – it represents the average return (or value) of the time series during the observed period when all dummy variables are equal to zero. If dummy variables are used for only four weekdays (e.g., Tuesday through Friday, with Monday as the baseline), then α represents the average return on Monday – i.e., the return when no specific weekday effects are present.

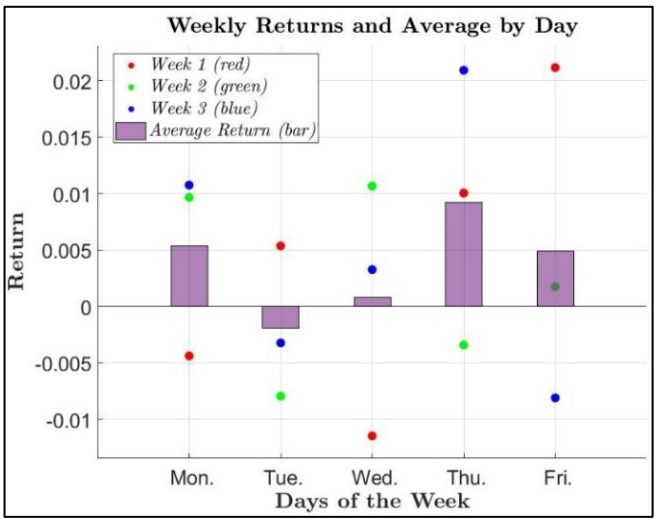


Figure 5. Example of asset returns on different weekdays (Matlab v.2018a).

3. Materials and Methods

While previous studies have explored the use of LSTM networks or spectral analysis individually for time series forecasting [69,70], the novelty of this study lies in the development and application of a hybrid model that integrates both techniques in a structured and complementary manner. The model is trained on synthetic time series with controlled cyclical components and stochastic noise, allowing for a clear evaluation of each model's capacity to detect cycle frequency, period, and amplitude. Additionally, a distinctive contribution of this approach is the use of the Discrete Fourier Transform on the residuals of the LSTM predictions, which serves to uncover latent frequency patterns that remain undetected by the neural network alone. This dual-layer approach – prediction plus residual spectral analysis – offers a new perspective on enhancing the interpretability and robustness of machine learning models in financial cycle detection.

Recurrent Neural Networks (RNNs) are a type of ANN used for tasks involving classification, clustering, and pattern recognition in data. They are particularly well-suited for identifying patterns and cyclical dependencies in complex, nonlinear data such as those found in financial markets. The main idea behind RNNs is that they have an internal state (memory), which allows information from previous steps to be carried forward to subsequent computations. Their architecture includes feedback loops to previous layers: the output from the current state is used as input for the next state (Figure 6).

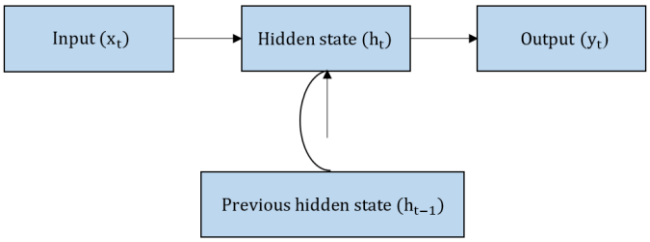


Figure 6. General architecture of a RNN.

In practice, the input x_t at each time step t is processed together with the previous internal state h_{t-1} to produce a new state h_t, and optionally an output y_t:

$$h_t = f(W_h h_{t-1} + W_x x_t + b),$$
$$y_t = g(W_y h_t + c), \quad (14)$$

where f and g are nonlinear functions (e.g., $tanh$, $ReLU$, or $sigmoid$), and W_h, W_x, W_y are weight matrices whose optimal values are learned during training.

With their structure and functionality, RNNs process data sequentially, using information from previous elements in the sequence. The RNN retains context from past time steps, making it well-suited for tasks where previous information is important.

4. Analyzing Cyclicality Using a Hybrid Model of RNNs Combined with Spectral Analysis via Fourier Transforms

To study market cyclicality, we developed a RNN model. Initially, we trained the RNN on a simulated cyclic market pattern to evaluate its ability to accurately determine the frequency and period of each cycle, as well as the amplitudes within individual cycles. The simulation of the cyclical market was defined using sine functions and random noise components:

$$Y = \sin\left(\frac{2\pi t}{20}\right) + \frac{1}{2}\varepsilon(n), \quad (15)$$

where t is the time step, and n is the number of observations The function $\varepsilon(n)$ adds noise to the data by generating a square matrix of dimension $n \times n$ filled with random values following a normal distribution $N(\mu = 0, \sigma = 1)$. This is implemented using the $randn$ function in Matlab v.2018a.

In the simulation defined above, the period is clearly $T = 20$, and the frequency is $\nu = 1/20 = 0.05$. The key question we pose is whether ANNs can capture these two parameters. The amplitude of the simulated market movement is adjusted through the stochastic nature of the term $1/2\,\varepsilon(n)$, which introduces noise into the data – and it was this component that we expected to challenge the models.

The time series data generated by equation (15) are formatted to be usable by the RNN for training and prediction – input-output sequences are created. The input sequence is a series of values fed into the RNN. It may consist of previous input values (e.g., values from $t = 1$ to $t = 10$). The output sequence is the target value Y that the RNN must approximate (predict). For instance, if the input sequence consists of values from $t = 1$ to $t = 10$, then the output sequence is the value of Y at $t = 11$.

The goal of creating input-output sequences is for the ANN to learn to recognize patterns in the input sequence in order to predict the next value in the output sequence. This process of forming input and output sequences is a fundamental step in time series modeling, allowing the ANN to learn how current values (input sequences) affect future values (output sequences).

In a separate supporting array, all values of the time series are stored. These are used as the target values for training. Since the LSTM networks in the software we use expect input data in cell array format, we convert the data from a numerical array into a cell array.

The RNN used in this study is of the LSTM type, specifically designed for working with sequential data such as the time series used in our case. We equipped the RNN with an internal structure that allows it to retain information over long periods of time, effectively avoiding the vanishing gradient problem commonly encountered in standard RNNs.

The LSTM network employs "input," "forget," and "output" gates to control which information should be retained or discarded. This makes the LSTM network highly effective for tasks such as time series forecasting. The LSTM network uses the input sequence to learn the dependencies between points in the time series. It then compares its forecast of the output sequence with the actual values in Y to calculate the error and adjust itself accordingly. After training, the ANN uses a new input sequence to predict the next value in the series, and so on.

In the hybrid model, we integrated the Discrete Fourier Transform to work in conjunction with the RNN:

$$X(f) = \sum_{t=1}^{N-1} x(t) e^{-\frac{i^2 2\pi f t}{N}}, \quad (16)$$

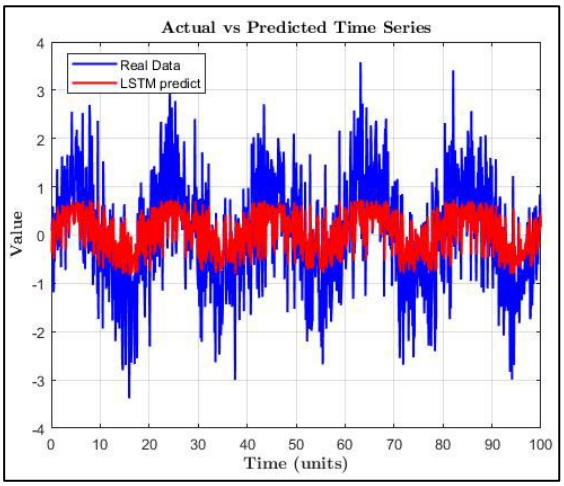
where:

- $X(f)$ is the amplitude of the frequency component f;
- $x(t)$ is the value of the time series at time t;
- N is the number of observations in the time series;
- i is the imaginary unit ($i^2 = -1$).

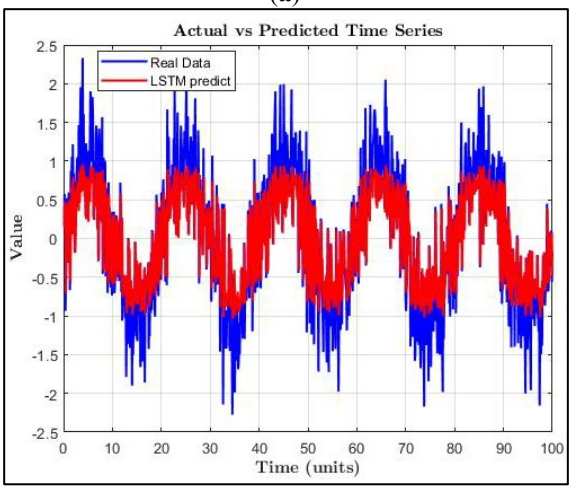
In practice, this mechanism is used to analyze the residuals (i.e., the differences between the actual

values and the RNN's predictions) in order to detect the presence of repeating cycles (frequency components).

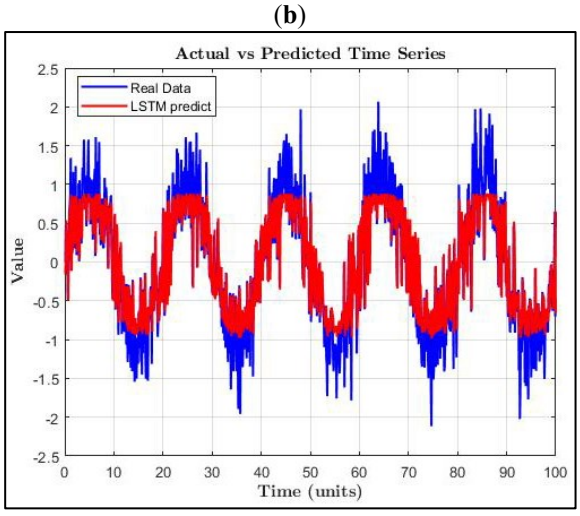
Figure 7 presents the results of the LSTM network with a single input layer (receiving the time series), one LSTM layer with hidden neurons, a connecting layer, and an output layer where the results are obtained. Increasing the number of neurons in the hidden layers improves the LSTM's forecasting capabilities.



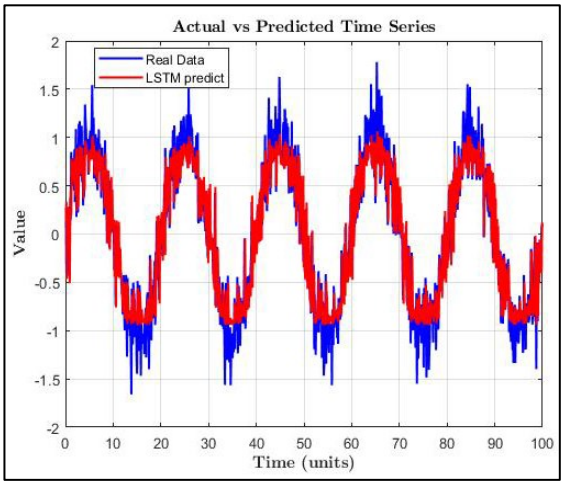
(**a**)



(**b**)



(**c**)



(**d**)

Figure 7. Simulated random time series and results of RNNs with different numbers of hidden neurons in the LSTM layer: (**a**) 25 hidden neurons; (**b**) 50 hidden neurons; (**c**) 120 hidden neurons; (**d**) 253 hidden neurons (Matlab v.2018a).

To enable a fair comparison of how the number of neurons affects approximation performance, all RNNs were trained using the Adam optimizer for 200 epochs. The transfer functions are built into the structure of the LSTM networks. For the input, output, and forget gates, the sigmoid function is used to constrain values between 0 and 1:

$$\sigma(x) = \frac{1}{1+e^{-x}}. \tag{17}$$

For generating candidate values for the cell state, the hyperbolic tangent function is used to constrain values between –1 and 1:

$$\tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}. \tag{18}$$

The numbers of hidden neurons (25, 50, 120, and 253) were selected to represent a progressive increase in model complexity, enabling us to assess how the depth of the LSTM layer affects the network's ability to capture amplitude variation in cyclical patterns. The initial values (25 and 50) represent smaller architectures often used in earlier studies for time series forecasting tasks, while 120 and 253 were chosen based on preliminary tests showing that beyond 200 neurons, performance improves marginally but at the cost of computational time. This range also allows for clear visual comparison of model behavior under increasing representational power.

The choice of 200 training epochs was made empirically: during initial trials, convergence of the loss function was observed well before epoch 200 in all configurations, with no signs of overfitting. This value offers a stable benchmark to compare performance across network sizes and optimizers. As for optimization algorithms, Adam was selected as the

primary optimizer due to its proven performance in training recurrent models, while Stochastic Gradient Descent (SGD) was used for comparison, illustrating differences in convergence dynamics and loss values. These choices align with common practices in machine learning and provide a robust basis for evaluating model performance.

What was established at this preliminary stage is that increasing the number of hidden neurons improves the RNN's performance. Almost all ANNs performed very well in identifying the period (and therefore the frequency) of the signal, while capturing the amplitude of market movement posed a challenge for LSTM networks with fewer hidden neurons. Increasing the number of neurons enhances the ANN's ability to handle amplitude variations, resulting in reduced prediction error. Figure 8 presents the loss function of the RNN with 253 hidden neurons in the LSTM layer.

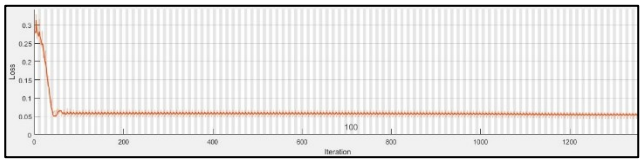


Figure 8. Behavior of the loss function during training (Matlab v.2018a).

The loss function used was the unweighted mean squared error (MSE):

$$Loss = MSE = \frac{1}{n}\sum_{i=1}^{n}(y_t - \hat{y}_t)^2. \quad (19)$$

where:

- n is the number of time periods,
- y_t is the actual market value,
- $\hat{y}_t$ is the value predicted by the RNN.

For the RNN with 253 hidden neurons in the LSTM layer, the final value of the loss was 0.058. Interestingly, the RNN precisely captured the period and frequency of market movements, reporting $T = 20, \nu = 0.05$. The error is primarily due to discrepancies between the actual and predicted amplitudes in the individual market cycles.

During experiments involving different training algorithms, it was found that the optimization algorithm either fails to converge for the problem under consideration, or – if it does converge – it has little effect on the final result, influencing primarily the convergence speed instead (Figure 9).

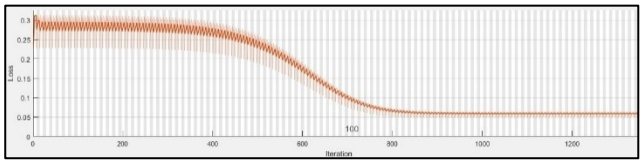


Figure 9. Loss function under stochastic gradient descent (Matlab v.2018a).

The final mean squared error when using the stochastic gradient descent algorithm was 0.061. Once again, the period and frequency were identified with high accuracy, with $T = 20, \nu = 0.05$. The error was primarily due to inaccuracies in predicting the amplitude of market movements within individual cycles.

The conclusions that can be drawn at this preliminary stage – based on simulated market cyclicality – are that RNNs are quite successful in capturing the cycle period, which also implies successful detection of its frequency. However, amplitude appears to be a more challenging aspect for the RNNs to predict accurately. Still, as the ANN architecture becomes more complex, its effectiveness improves, and this issue can potentially be addressed with satisfactory precision.

Additionally, it was found that the Adam optimizer is the most suitable training algorithm for the problem studied. Other converging algorithms mainly affect the speed of convergence to a local minimum of the error, rather than the final prediction result.

5. Conclusion

The study of cyclicality in capital markets is of great importance to financial analysts, investors, and economists. Understanding cyclical patterns enables more accurate forecasting of market movements, which is critical for making timely and informed investment decisions. On the other hand, recognizing cyclicality helps investors identify periods of high volatility or weakness, allowing them to adjust their market exposure accordingly. Upward and downward cycles present favorable opportunities for buying or selling assets, and familiarity with these patterns can even assist in synchronizing investment strategies.

In the conducted study, a LSTM was used in combination with spectral analysis based on the Discrete Fourier Transform. This hybrid architecture was chosen due to the ability of LSTM networks to capture temporal dependencies, and the capability of spectral analysis to identify frequency components in market data. LSTM networks have proven to be effective in processing time series, while spectral analysis enables the detection of cyclical components that might otherwise remain hidden. The experiments conducted demonstrated the applicability of this hybrid model for studying the cyclicality of financial markets.

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