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FOREX rate prediction improved by Elliott waves patterns based on neural networks

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ABSTRACT

Financial market predictions represent a complex problem. Most prediction systems work with the term *time window*, which is represented by exchange rate values of a real financial commodity. Such values (time window) provide the base for prediction of future values. Real situations, however, prove that prediction of only a single time-series trend is insufficient. This article aims at suggesting a novelty and unconventional approach based on the use of several neural networks predicting probable courses of a future trend defined in a prediction time window. The basis of the proposed approach is a suitable representation of the training-set input data into the neural networks. It uses selected FFT coefficients as well as robust output indicators based on a histogram of the predicted course of the selected currency pair. At the same time, the given currency pair enters the prediction in a combination with another three mutually interconnected currency pairs. A significant output of the articles is, apart from the proposed methodology, confirmation that the Elliott wave theory is beneficial in the trading environment and provides a substantial profit compared with conventional prediction techniques. That was proved in the performed experimental study.

1. Introduction

Economic and financial systems belong to complex, dynamic systems as society creates phenomena with a significant degree of chaotic behavior. In such cases, it is difficult to carry our prediction. Therefore, advanced methods are used to provide better results. Such methods primarily include softcomputing methods (fuzzy logic, artificial neural networks, evolution algorithms) that can be used either individually or combined. For instance, neural networks and conventional time series techniques have been a subject of numerous works. The benefit of neural networks compared with more traditional econometric models is that neural networks flexibly model complex, possibly nonlinear relationship with no presumption of the underlying data-generating process. The primary use in the economic and financial area is held by the prediction of the future development of financial and economic indicators in macro and microeconomy, predictions of values of stocks and shares, commodities, indexes, currencies, etc.

At the beginning, it is necessary to state that a financial time series is a collection of chronologically recorded observations of the financial variable(s). Financial time series prediction is a very complex task as a financial time series shows these characteristics (Pradeepkumar & Ravi, 2018): 1. Financial time series frequently act as a random-walk process, making the prediction almost impossible (from a theoretical point of view). 2. Financial time series are usually very changeable, i.e., there is a large amount of random (unpredictable) day-to-day variations. 3. Statistical characteristics of the financial time series differ at various points in time as the process varies over.

Time series prediction involves gathering past observations of a variable, their analysis in order to create a model grasping the underlying process of data generation and utilization of such a model to predict the future. The usage of artificial neural networks for financial prediction is not new. A neural network performs the following functional mapping (1):

$$y_t = f\left(y_{t-1}, y_{t-2}, \dots, y_{t-p}, \theta\right) \tag{1}$$

where y_t is the observation at time t, p is given number of previous values, θ is the vector of network weights. Thus, the artificial neural network (ANN) is equivalent to a nonlinear autoregressive model for time series forecasting problems. Several design factors significantly impact the accuracy of neural network forecasts. These factors include the selection of input variables, preparing data, and network architecture. There is no consensus about these factors. In contrast to traditional forecasting methods, neural networks' techniques are able to gain a nonlinear relationship among relevant factors with no prior knowledge about the input data distribution (Atsalakis & Valavanis, 2009).

In the last years, many researchers try to develop various methods to support decision making in the financial market. In

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these scientific works, there is a lot of works that examine the use of neural networks' techniques to solve financial market problems. Several reviews of financial time series prediction using neural networks are described for example in Bahrammirzaee (2010), Elmsili and Outtaj (2018), Huang, Lai, Nakamori, and Wang (2004), Katarya and Mahajan (2017), Li and Ma (2010), Tealab (2018) and Yu, Wang, Huang, and Lai (2007), etc. According to Martinez, da Hora, Palotti, Meira, and Pappa (2009), the majority of works have used successfully backpropagation neural networks for solving the financial forecasting problem, but the current research is primarily focused on financial time series forecasting with deep learning (Sezer, Gudelek, & Ozbayoglu, 2020). However, neural networks work as a black box because they do not show interactions with the environment to receive outcomes. The contribution of this paper is the prediction of financial markets using appropriately chosen FFT coefficients in order to represent important properties of time series, in particular salient market trends in different time frames. An equally important contribution is the results of an experimental study that confirms that the use of Elliott wave theory yields observable financial gains in real trading compared to the use of prediction independent of the conclusions of Elliott patterns. Literature research in this area is the subject of the next chapter.

2. Related works

FOREX (Foreign Currency Exchange) is an abbreviation for the foreign exchange market where currencies are traded (Edwards, 2014). An exchange rate is expressed as a ratio of two currencies. Exchange rates belong to the most important economic indexes in the international monetary markets. Exchange rates are influenced by many highly correlated economic, political, and also psychological factors that interact in a very complex way. In the literature, different methods based on neural networks have been used for FOREX price predictions, including recurrent neural network, convolutional neural network, deep neural network, multilayer perceptron, etc. Sezer et al. (2020) described the details of implementing such models in a comprehensive comparative study. Yu et al. (2007) provide an overview of articles dated 1971 to 2004, neural networks are used for FOREX rate prediction. The work of Li and Ma (2010) presented a comparative survey of hybrid intelligent systems including exchange rate prediction based on neural networks. Since a neural network is regarded as having a great potential of a powerful prediction tool, its combination with other technologies increase its global performance. The authors (Zhang & Berardi, 2001) developed an apparatus of neural networks with more promising results in FOREX predictions than simple neural networks solving the same tasks. The authors (Chen & Leung, 2004) brought in a two-phase hybrid model to correct errors in FOREX predictions. At first, they estimated FOREX rates and then the neural network corrected the resulting error. The authors concluded that the proposed model achieved high prediction accuracy. In Yu, Lai, and Wang (2008) is predicted FOREX rate using an RBF neural network ensemble. In the ensemble, there were first many single RBF networks produced and then some of these networks were selected to form an ensemble. The authors claim that their model improved FOREX predictions. In Majhi, Rout, Majhi, Panda, and Fleming (2012) is proposed the Wilcoxon norm-based neural network, which estimates such weight values that is able to deal with outliers in time series in order to successful forecasting. The performed experimental study was dealt with the following exchange rates: British Pound (GBP), Japanese Yen (JPY), and Indian Rupee (INR). Authors (Zhang, Shen, & Zhao, 2014) proposed a hybrid model combining fuzzy granulation with continuous-valued deep belief networks for predicting the fluctuation range of FOREX rate. The authors stated that their model is more efficient compared to classical approaches. Authors (Shen, Chao, & Zhao, 2015) implemented a Deep Belief Neural Network and the conjugated gradient method for the neural network adaptation for the purpose of prediction the following weekly exchange rates of British Pound (GBP) and US Dollar (USD), Brazilian Real (BRL) and US Dollar (USD), and Indian Rupee (INR) and US Dollar (USD). The received outcomes were compared with results from a multilayer perceptron (MLP), the ARMA model and the random walk (RW). Authors stated that their proposed model had much more accurate predictions than the other models. After reviewing 26 various ANN-based hybrids, the authors (Pradeepkumar & Ravi, 2018) concluded that concerning the FOREX rate prediction, the multi-layer perceptron (MLP) was the most often used architecture probably because of its universal approximator property. In the work Galeshchuk and Mukherjee (2017), authors dealt with an overview of deep networks for predicting the direction of change in foreign exchange rates. They studied the ability of deep convolution neural networks to predict the change rates direction in FOREX rates. They stated that the recent success of deep networks is partly caused by their ability to learn abstract features from original data. The experimental study was performed over exchange rates for the currency pairs EUR/USD, GBP/USD and JPY/USD. The obtained experimental results demonstrated that used deep neural networks achieved significant classification accuracy in predicting the direction of change in forex rates. In Durairaj and Mohan (2019) is presented a comprehensive review of deep learning-based hybrid forecasting models during 1999–2019. Authors studied 34 different deep learning-based financial time series predictions including predicted of FOREX rate. The following sections describe the proposed model, provide the achieved results, and discuss the meaning of those results.

3. Theoretical background

3.1. Fourier transform

The Fourier transform (FT) is an integral transformation converting the signal between time and frequency dependent expression using harmonious signals, i.e. the sin and cos functions, thus a complex exponential function in general. It serves to convert signals from the time area into the frequency one. The signal can be either in continuous or discrete time (Chu, 2008).

Definition. Let $f(t)$ be a real or complex function with a real variable t. Then, its Fourier transform $\hat{f}(t)$ with a real variable v is defined as (2),

$$\hat{f}(v) = \int_{-\infty}^{\infty} f(t)\, e^{-2\pi i v t} dt \tag{2}$$

where t represents the time and v represents the frequency. $\left|\hat{f}(v)\right|$ is often called the spectrum and states how much energy function $f(t)$ contains in frequency v.

The Inverse Fourier transform is given by the relationship (3) and converts the signal from the frequency domain to the time one:

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(v)\, e^{2\pi i v t} dt \tag{3}$$

Therefore, $f(t)$ and $\hat{f}(t)$ create a Fourier pair representing the same underlying identity.

If we generalize Eq. (2) for a discrete example, holding that the input signal $f(t)$ equals a discrete sequence of complex numbers

$f(t_k) = \{f_0, f_1, \ldots, f_{N-1}\}$, kde $f_k = f(t_k)$ pro $k = 0, 1, \ldots, N-1$, then the Discrete Fourier transform (DFT) is defined as (4):

$$F_k = \sum_{n=0}^{N-1} f_n e^{-\frac{2\pi i}{N} kn} \tag{4}$$

A Fast Fourier Transform (FFT) is an effective algorithm to compute the discrete Fourier transform and its inverse. The most used FFT variant is the Cooley–Tukey algorithm (Chu, 2008), which recursively divides the DFT sizes $N = N_1 \cdot N_2$ into smaller transforms of size N_1 and N_2. While taking grounds in the relationship (1), i.e. predicting future data based on the historical one, a fundamental problem with the time unit of the given financial series arises. Generally, time windows of 1 min, 5 min, 15 min, or 60 min are used. If we overlap the course in other time windows within the same time length, the result will obviously be the same course of the time series, yet it differs more as the length of the time window get smaller. In other words: the course is almost identical in lower frequencies whereas it differs in high frequencies, see Fig. 1. The FFT converts the time domain into the spectral domain, where the first coefficient, referred to as the DC coefficient, represents the DC component of the signal. All other coefficients, referred to as AC coefficients, represent the individual amplitudes of the frequency components of the AC signal. Using the FFT, we achieve relative independence of the used time window as well as we provide space for a variable time length, see Fig. 2.

3.2. Elliott wave

Technical analysis is one of the known and interesting ways to analyze markets. However, it often splits traders as there are many approaches to how to read market graphs. Some focus on repeating patterns, others compare other parameters. But there is also a controversial, but functional, theory — the theory of Elliot waves. It states that moves on financial markets show one feature, repetition. These moves are called waves. The whole theory can be beneficially used for any trading time interval, either short-term, medium-term, or long-term. Even the authors (Volna, Kotyrba, & Jarusek, 2013) applied this theory on other courses, particularly Volume courses, which denote the trade liquidity over a time unit. The authors showed that the Elliott Wave Theory can be applied and used on significantly different types of time series. Market cycles are reactions of investors to external factors or prevailing mass psychology. The result of the whole theory is that if one can correctly identify repeating shape patterns, they can predict future development.

Impulses and corrections

Prices tend to fluctuate in impulse or correction waves. If we know in which wave the current price is and what the recent waves have been, it helps us predict the future development of the price. An impulse wave (1–2–3–4–5) is a significant price move connected with the trend. A growing trend achieves higher price levels as a move up is bigger than down, which appears between the waves up. Conversely, correction waves (a–b–c) are smaller waves appearing inside the trend. They can be seen in Fig. 3.

The overall idea is simple — one should buy during reverse moves or correction waves in a growing trend and keep to another impulse wave as long as the price grows. On the other hand, one should enter into a short position during correction waves in a downtrend and profit from another impulse wave downwards. The concept of impulse and correction waves is also used to determine the trend direction. If there are significant moves up with small correction waves in between followed by a noticeable move down, it signalizes the growing trend to end. As impulses appear in the direction of the trend, a significant move down, which is bigger than the previous correction waves and as big as the impulse waves up, it implies a trend going down. If the trend is going down and a huge wave up, which is as big as the previous wave down in the downtrend, appears, the trend has now turned into a growing one and traders should start looking for opportunities to buy in the next correction wave.

The Elliott Wave Theory is based on the following principles:

- Each impulse is followed by a correction reaction
- Five waves (1–2–3–4–5) in the direction of the main trend are followed by three corrections (a–b–c) or a 5 : 3 move
- Move 5–3 terminates the cycle

An important finding is that the theory founder discovered that those moves are fractals. What does it mean? One impulse wave contains another five waves in a smaller scale. Let us have a structure of 5 waves in a one-week graph. According to the theory, each impulse wave will consist of 5 smaller waves while a correction wave will compose of another 3 waves. This process will be repeated again and again. Nowadays, the whole theory is much more complex and R&D has newly identified lots of rules and directions to follow when classifying waves to ensure correct the future predictions. According to the theory, wave 2 is 61.8% of the length of wave 1. Even next phases show this interesting ratio of impulse and correction waves. This ratio is often related to the so-called golden ratio. The Elliott Wave Theory as a whole is not an easy concept, but it requires time for understanding and even more for its correct use. Many traders use rules derived from the Elliott Wave Theory, combine them with other technical–analytical tools, and thus increase the probability of a successful setting of their technical analysis (Chandar, 2019; Duan, Xiao, Yang, & Zeng, 2018; Volna et al., 2013).

3.3. Multilayer artificial neural network

Each artificial neural network (ANN) composes of formal neurons that are mutually interconnected in a way that the output of one neuron is the input into (generally more) neurons. The most spread neural network model is a multilayer feedforward neural network, where neurons are divided into layers and connections between neurons lead only from lower to higher layers (Cain, 2016). Distribution and processing of information in the network is enabled by the change of the state of the neurons lying on the path between the input and output neurons. The neural network develops in time, neurons change their state, weights are adapted. There are many adaptation algorithms for multilayer neural networks (Cain, 2016), e.g. backpropagation (BP), backpropagation with momentum, Levenberg–Marquardt algorithm (LMA), Quickprop, Parallel Resilient Backpropagation (Rprop) etc. The proposed model takes advantage of a multilayer feedforward neural network adapted by the Parallel Resilient Backpropagation (Rprop) method, thus we are going to describe this adaptation in more detail. Rprop belongs to currently the fastest available training algorithms. Its work is similar to backpropagation although the weights are updated depending on the error gradient sign (Prasad, Singh, & Lal, 2013). The size of the weight change Δw_{ij} on connections between units i and j is determined as follows (5):

$$\Delta w_{ij}(t) = \begin{cases} -\Delta_{ij}(t), \text{ if } \frac{\partial E}{\partial w_{ij}}(t) > 0 \\ +\Delta_{ij}(t), \text{ if } \frac{\partial E}{\partial w_{ij}}(t) < 0 \\ 0, \text{ else} \end{cases} \tag{5}$$

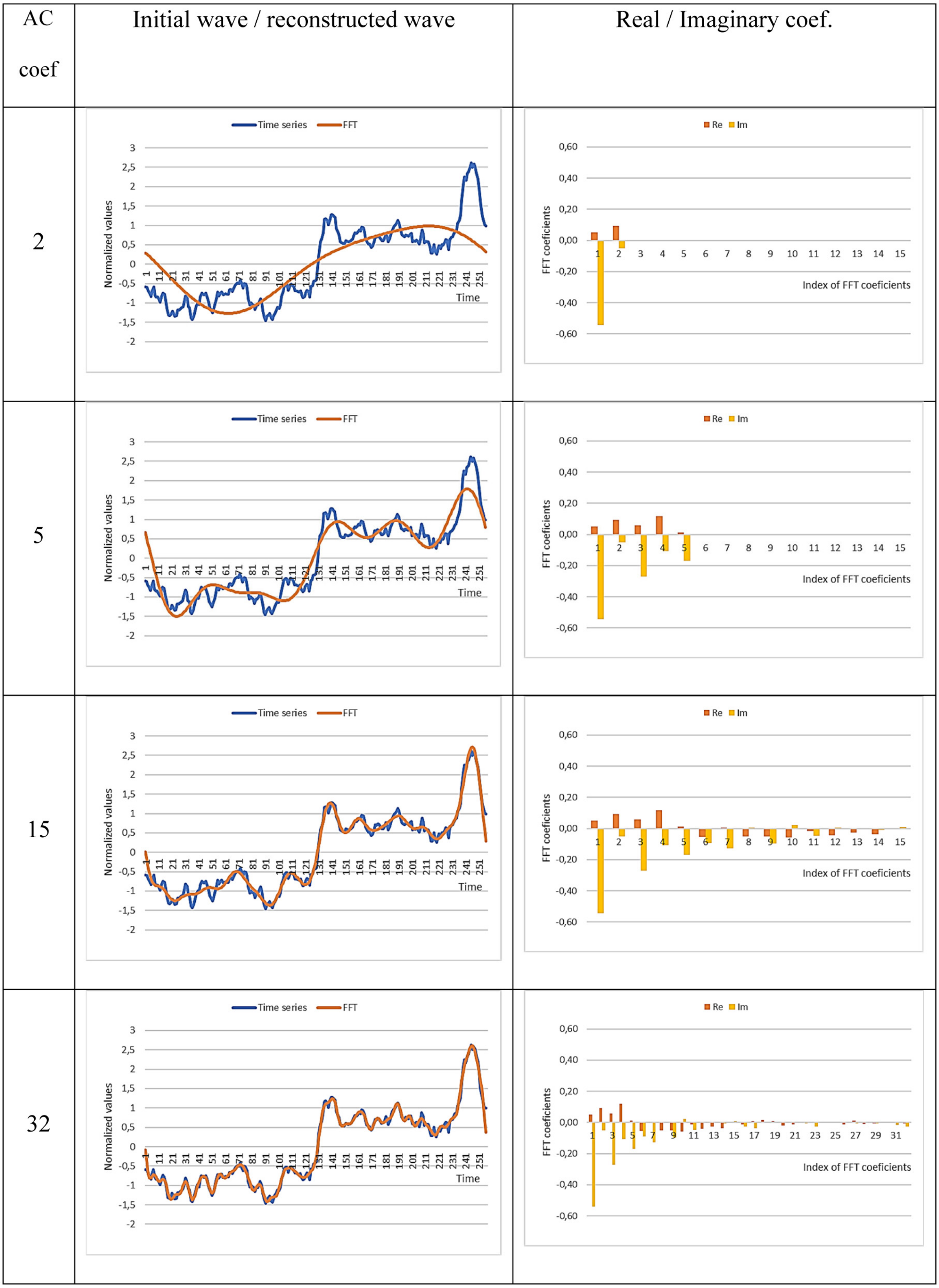

Fig. 1. Influence of the number of AC coefficients on the resulting wave approximation. The y-axis values are normalized according to (8).

where

$$\Delta_{ij}(t) = \begin{cases} \eta^{+} \cdot \Delta_{ij}(t-1), \text{ if } \dfrac{\partial E}{\partial w_{ij}}(t-1) \cdot \dfrac{\partial E}{\partial w_{ij}}(t) > 0 \\ \eta^{-} \cdot \Delta_{ij}(t-1), \text{ if } \dfrac{\partial E}{\partial w_{ij}}(t-1) \cdot \dfrac{\partial E}{\partial w_{ij}}(t) < 0 \\ \Delta_{ij}(t-1), \text{ else} \end{cases} \tag{6}$$

Values of the increase and the decrease factors are set as follows: $0 < \eta^{-} < 1 < \eta^{+}$. Δ_0 is the initial value of the delta update-value Δ_{ij}. The mean squared error function E (MSE) is represented as a distance between the target and the actual output vector (Prasad et al., 2013). The Rprop algorithm was selected for its advantages, namely accuracy, speed, and robustness.

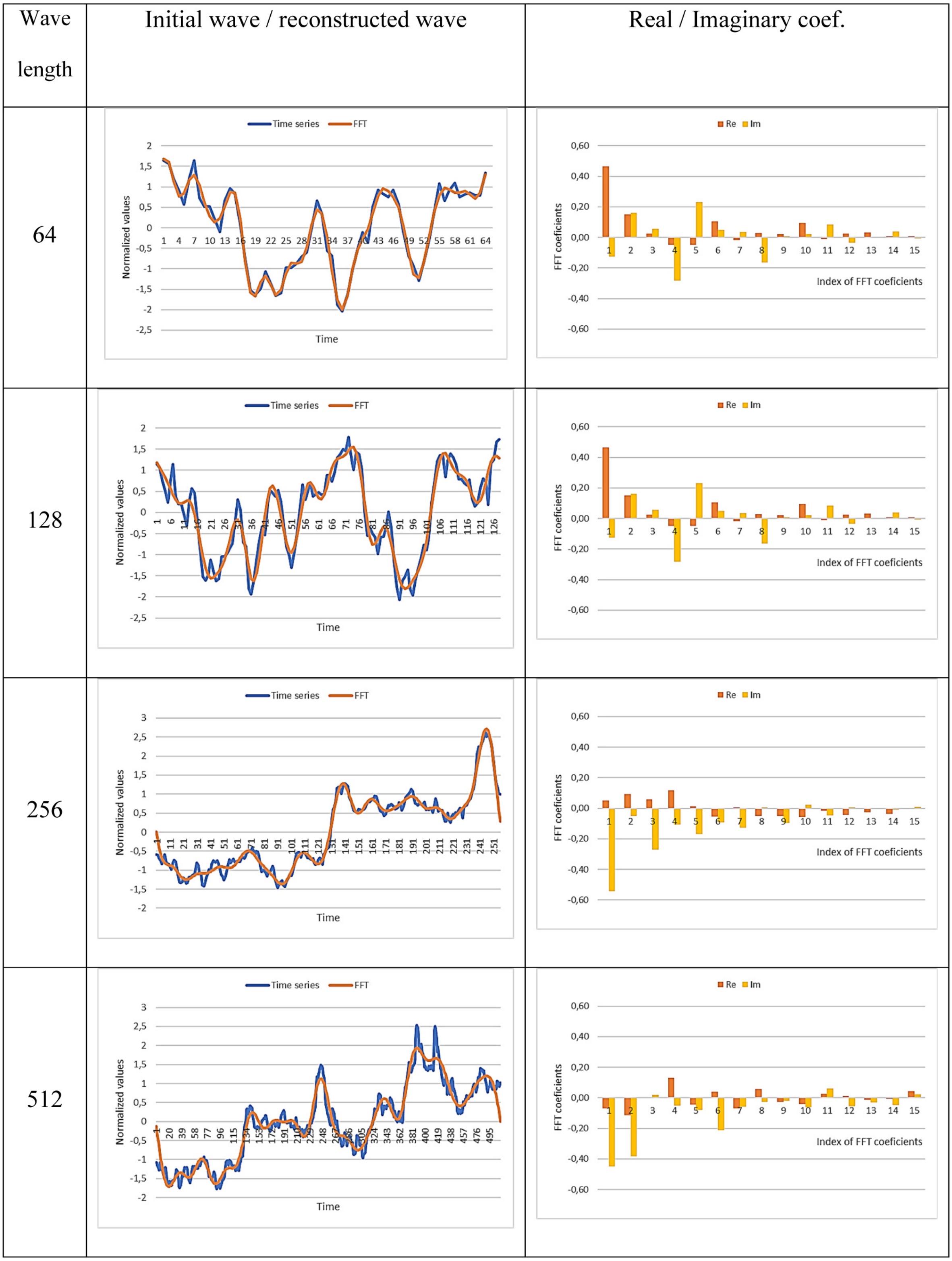

Fig. 2. Representation of a variable length of a window using 15 AC coefficients.

4. The proposed model

The objective of the proposed method is to develop a prediction system to estimate the EUR/USD exchange rate at the FOREX market in a 60 minute time window. Training of the neural networks used input data in the form of 4 currency pairs belonging to the main ones and creating a closed cycle, i.e. EUR/USD, USD/JPY, CHF/JPY, and EUR/CHF. The training included the development of the exchange rates in the period 2015–2018 (one minute intervals) out of which 30,000 time windows were

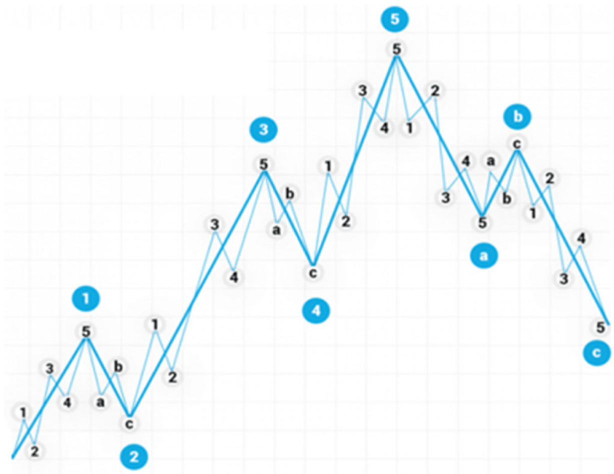

Fig. 3. Elliot Wave Theory.

selected (one window is 256 min). Then, the whole system was tested on randomly selected 300,000 unused developments in the period 2014–2020.

4.1. The first neural network

The first neural network was trained on 30 figures of Elliott waves (EW), see Fig. 4, which were interpolated to a vector of 256 components. Each vector was subsequently normalized.

The topology of this network was 30–30–30, where 30 input neurons represent the first 15 AC coefficients representing the NN input vector (30 components). Since we use 30 basic EW patterns, the output layer includes 30 output neurons. The output neurons represent the similarity of the produced pattern with one of the learned EW. The adaptation took advantage of the BP algorithm with a hyperbolic tangent activation function and learning coefficient 0.1. the adaptation was terminated with an error $E < 0.04$ and t needed app. 38,000 iterations.

4.2. The second neural network

Data representation and normalization

In order to be able to work with the data of individual pairs more, it was necessary to normalize it. We used a simple normalization form where a standard deviation was calculated over randomly selected time windows of 256 min and the resulting coefficient was calculated as an average of individual standard deviations, see Eq. (7).

$$N_{coef} = \frac{\sum_{i=1}^{N} \sqrt{\frac{1}{256} \sum_{j=1}^{256} \left(x_{ij} - \overline{x_i}\right)^2}}{N} \tag{7}$$

where

N_{coef} is the normalizing coefficient of the selected currency pair (EUR/USD, EUR/CHF, USD/JFY, and CHF/JPY)

N is the number of randomly selected windows of 256 values

x_{ij} is an element where i is the index of a randomly selected window, j is the index of the element in the window

$\overline{x_i}$ is the average value of the ith selected window

A randomly selected window is then normalized according to (8)

$$x'_{ij} = \frac{\left(x_{ij} - \overline{x}_i\right)}{N_{coef}} \tag{8}$$

where

x'_{ij} is the normalized value of the element

x_{ij} is the real value of the exchange rate

Table 1
Real normalizing coefficients of individual currency pairs.

Currency pair	Rate (avg. 2015–2020)[a]	N_{coef}
EUR/USD	1.133715	≈ 0.000751633
USD/JPY	109.524268	≈ 0.077926068
CHF/JPY	112.075919	≈ 0.083936098
EUR/CHF	1.107702	≈ 0.000482892

[a][cit. November 6, 2020] https://www.ofx.com/en-gb/forex-news/historical-exchange-rates/yearly-average-rates/.

$\overline{x_i}$ is the average of the selected vector

Real normalizing coefficients N_{coef}, average annual values of the exchange rate, and names of the used currency pairs are stated in Table 1

Thus, we obtained a tool for normalized representation of all 4 used currency pairs independent of the absolutes values of their exchange rates.

Preparation of input vectors of the training set

One of the fundamental visions of this work is an assumption that the Elliott Waves theory has real grounds and it can be successfully used in practice. Prediction of the proposed model is based on absorbing information from 4 parallelly developing exchange rates of 4 currency pairs in a window of 256 min. The Elliott theory states that if the given data shows a significant match with any of the EW figure, the future trend of the series will respond by a rise or a fall. Such vague information, however, does not say anything about a real future development of the time series. According to the proposed methodology, it holds that if we find a significant similarity (90%) with an Elliott wave from the training set of the first neural network, then such a time window (256 values) will be included in the training process of the second neural network. As the Elliott theory is defined exactly over one time series, a suitable training set selection must be in accordance with a high similarity of the predicted pair with some of the EW. Yet, the learning process encompasses all 4 series of the currency pairs. We work on the assumption that all pairs affect one another and non-standard behavior in the development of one pair is more likely than non-standard behavior of all 4 pairs at the same time.

The core of the proposed method is a feed-forward multilayer neural network adapted by the RPROP method. It is known that these types of neural networks are sensitive to a pattern offset, which is an inevitable phenomenon of time series. We found out experimentally that native representation of any time course (i.e. a mere sequence of individual discrete values) significantly complicate quality adaptation. Moreover, a pattern offset (for example by 1 min) can lead to completely different results in the forward phase. Therefore, all input vectors were represented by a reduced set of FFT coefficients for each time window and all 4 currency pairs. We used a random selection of 30,000 training sequences over one minute intervals of the exchange rate development of the 4 currency pairs. The sequences were 256 + 60 min long and dated to 2015–2018. 256 min serve to predict the following 60 min in the exchange rate development and they equally cover the times periods of the financial series throughout the year. FFT was performed over all 4 currency pairs. If FFT of the predicted pair is similar to FFT of any EW by at least 90%, such a window is included in the training set for the second neural network, where each currency pair and its FFT uses 15 AC coefficients. This results in the creation of an input vector of 120 components (4 × 2 × 15 = 120 input neurons). This transformation is performed with respect to the following reasons:

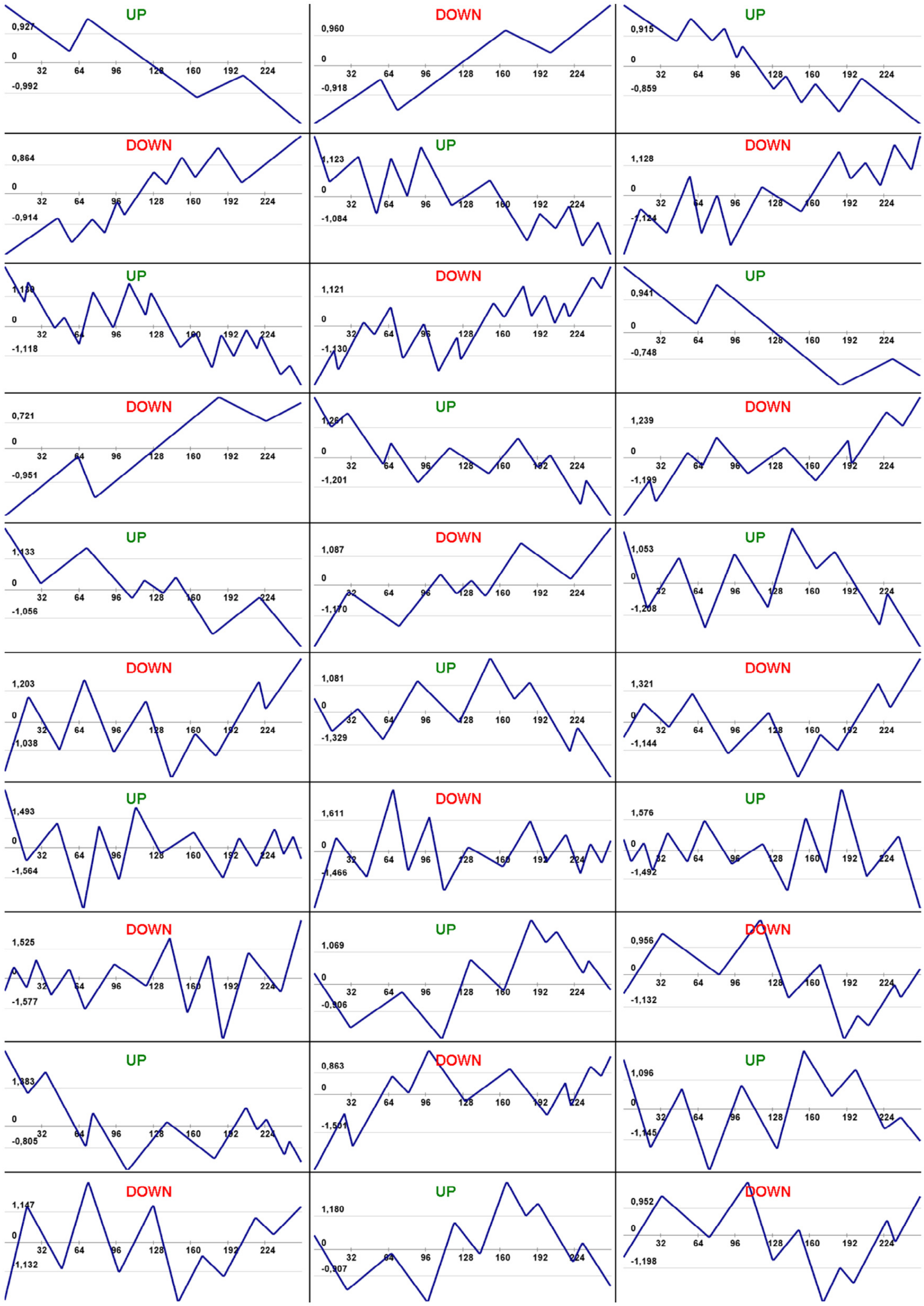

Fig. 4. Training set for the first neural network — 30 Elliott waves figures with trends marked UP (rising trend) and DOWN (falling trend).

- elimination of the time window offset impact
- Usage of only lower FFT AC coefficients keeps distinctive structural characteristics of time series and minimizes the impact of local extrema in time series (in fact it is analogy to averaging), see Fig. 1.

This approach is primarily beneficial as it eliminates the interpolation operation to the required number of input values into the neural network. In addition, such implementation corresponds with the theory of forex markets where "the more significant and

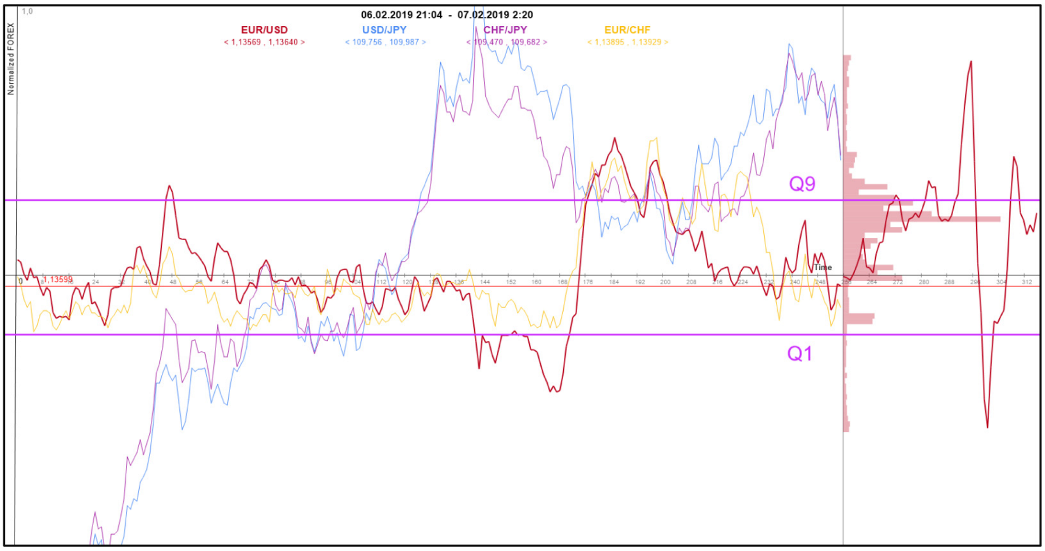

Fig. 5. Determination of the 1st and 9th percentile over the input values of the predicted currency pair (red color).. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

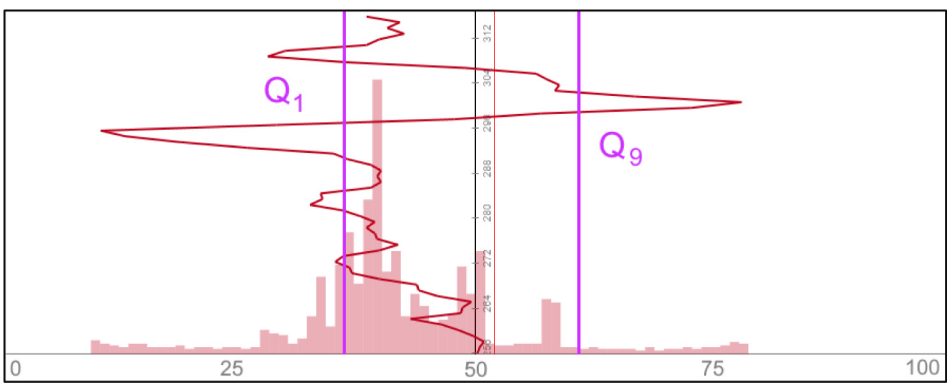

Fig. 6. Predicted time window.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

longer the trend is, the higher the influence is on future price movements" (Xiao et al., 2019).

Preparation of the training set output vectors

A frequent phenomenon is a situation when various prediction models represent their prediction only in one predicted development. According to our findings, it is an imperfection proving incomprehension of the given problem. A trend can rise or fall at one moment, but we presume that with a different probability. Thus, the output vector is constructed as a frequency histogram of the predicted wave occurrence in the predicted time window. The predicted part of 60 min was interpolated to 1200 points, which were then used to create a histogram of the development. In order to determine the histogram window (predicted part), we used the following procedure:

1. Determination of size L of the output vector — histogram (selected $L = 100$).
2. Ascend ordering of all values of the predicted pair output part (256 values), see Fig. 5 and finding the 1st and 9th percentile in the ordered sequence — Q_1 and Q_9.
3. Determination of the minimum and maximum histogram value according to formula (9).

$$\begin{aligned} \min_H &= -2 \cdot (Q_9 - Q_1) \\ \max_H &= 2 \cdot (Q_9 - Q_1) \end{aligned} \tag{9}$$

4. For each point P of the interpolated predicted part (i.e. 1200 points)
   a. let us find a corresponding index of the output histogram (i_H) according to formula (10),

$$i_H = round\left((L-1) \cdot \mathrm{Max}\left(0, \mathrm{Min}\left(1, \frac{P - \min_H}{\max_H - \min_H}\right)\right)\right) \tag{10}$$

   where $round\,(x)$ is a rounding function to the closest integer
   b. the histogram value i_H is increased by 1.
5. The whole histogram is normalized according to the maximum value from L values of the output vector according to formula (11).

$$i'_H = \frac{i_H}{\max\,(H)} \tag{11}$$

The red color in Fig. 6 depicts real values of the time series whose development will be predicted. The histogram (light red color) represents normalized values of the predicted development, which is the output vector of the second neural network.

Adaptation

The resulting neural network with the hyperbolic tangent activation function has the topology 120–120–100–100. The RPROP method was selected for adaptation. The adaptation was terminated after 2000 iterations with a substantial error 1.5. the reasons of an incomplete adaptation of the network can be primarily seen in the number of contradictory training vectors (we require more different outputs to one input and the neural network tries to adapt in the form of generalization rather than to fully learn the given pattern) (Zhang, Bengio, Hardt, Recht, & Vinyals, 2016).

We also experimented with other adaptation algorithms. The backpropagation method adaptation (Rumelhart, Hinton, & Williams, 1986) was successful, but learning took an incredibly long time. The Levenberg Marquardt algorithm (Levenberg, 1944) terminated during the learning process by exhausting the system resources (it ran out of the RAM memory).

Prediction process — active phase

The whole system was tested on 300 thousand randomly selected unused currency pairs dated 2014–2020 aiming at predicting the future development of the exchange rate of the given currency pair, e.g. EUR/USD.

The prediction process takes place in the following steps:

1. Time windows of 256 minute-size were randomly selected from the period 2014–2020.
2. The time windows for all currency pairs were normalized using a standard deviation used in the learning process, Eq. (8)
3. The time windows were converted to FFT, see Fig. 1.
4. The first 15 FFT AC coef. were used from each time window.
5. If there was a 90% and more match of the first neural network (Elliott wave) with the predicted pair (Fig. 4), such a window was sent to the second neural network. The output of the second neural network provides a histogram of the predicted development.
6. The histogram is divided into 2 parts according to the last exchange rate value in the not-predicted (input) part, see Fig. 7.

    a. If the count of the histogram values in the upper part (above the line of the last exchange rate) is significantly higher (**striking difference**) than the count of the values in the lower part (below the line of the last exchange rate), then we predict a rising trend.
    b. If the count of the histogram values in the upper part (above the line of the last exchange rate) is significantly lower (**striking difference**) than the count of the values in the lower part (below the line of the last exchange rate), then we predict a falling trend.

Fig. 8 depicts FFT time series and Elliott waves from Fig. 7 at 96% similarity.

In Fig. 7, four time windows of the currency pairs (EUR/USD, EUR/CHF, USD/JFY, and CHF/JPY) enter the prediction, the EUR/USD pair is depicted in red. The similarity of the development of this currency pair with an Elliott wave is 95% (the Elliott wave is in dark blue). The green color (histogram) shows the second neural network prediction in a 60 minute horizon for the predicted pair EUR/USD. The green figures indicate the count of areas above and below the last exchange rate value.

Fig. 9 provides a detailed prediction of the future development of the currency pair. The green color represents the states of the second neural network output neurons. The red color marks the real development of the time series and the red columns represent its histogram. In this particular case, the trading is taking place as the count of the areas (**19.271**) of the green histogram above the line of the last exchange rate (left to the red line) is significantly higher than the count of the areas (**8.023**) of the green histogram below the line of the last exchange rate (right to the red line).

5. Experiments — trading system

Objectives of the experimental study

The experimental study was aimed at verification whether the real trading of the proposed system will generate profit or loss. It is essential to remark that the presented simulation does not count with trading fees required by most brokers. Next objective of the performed experimental study was to verify if the use of the Elliott Waves theory provides improvements in trading results. Therefore, the whole study was divided into two parts. The first part of selecting the suitable time for trading uses metrics based on the similarity of an Elliott wave to the values of the time series of the predicted currency pair. In the second part of the experimental study, the time for trading is selected randomly. Both the first and second parts of the experimental study take advantage of the prediction abilities of the second neural network. The parameters of the used neural networks are stated in Table 2.

In order to experimentally verify the proposed model, it is necessary to create a basic trading system and trade with all recommendations provided by the neural network. Based on such recommendations of the neural network, the trading system enters a short (selling) or long (purchasing) position. Each trading system should encompass the following four key components (Bhagwati, 2014):

- *Initial strategy*. One of the crucial steps is to select a good initial point in the graph with the highest success probability.
- *Stop Loss* (SL) is a protection trading order to limit possible losses from an open position. This order is automatically executed when a certain price or loss level is reached. SL is placed either to limit losses or to make a profit. In our proposed trading system, SL is set as a fixed value for sort and long position and it is invariable in the open position.
- *Take Profit* (TP) is a trading order terminating a trading position in a profit without trader's interference. The order is automatically executed when the price achieves a certain level.
- *Money Management* (MM) is a strategy telling the trader where to place Sl and TP, i.e. it determines the loss level that can be afforded in each trade. MM enables the trader to control risks.

Parameters of the used trading systems are stated in Table 3.

The values of the SL and TP coefficients were determined experimentally. They stem from the fact that in a 60 minute interval, the average development of the USD/EUR exchange rate is equal to such values. In practice, trading takes place 20 min on average. The trading results are depicted in Figs. 10 and 11. The trading simulation includes 30,000 randomly selected trading positions from 2014–2020 and the simulation parameters are stated in Table 3.

Figs. 10 and 11 show that in the case of random trading (yellow color), we oscillate in areas close to a zero profit. During prediction without Elliott waves (green color) for a suitable trade, the trade continually rises, on average **1.1** dollar per trade. During prediction using Elliott waves (red color) for a suitable trade, the trade continually rises, on average **1.5** dollar per trade. It is obvious that using the EW apparatus brought a prediction increase (in USD per trade) by **39%**.

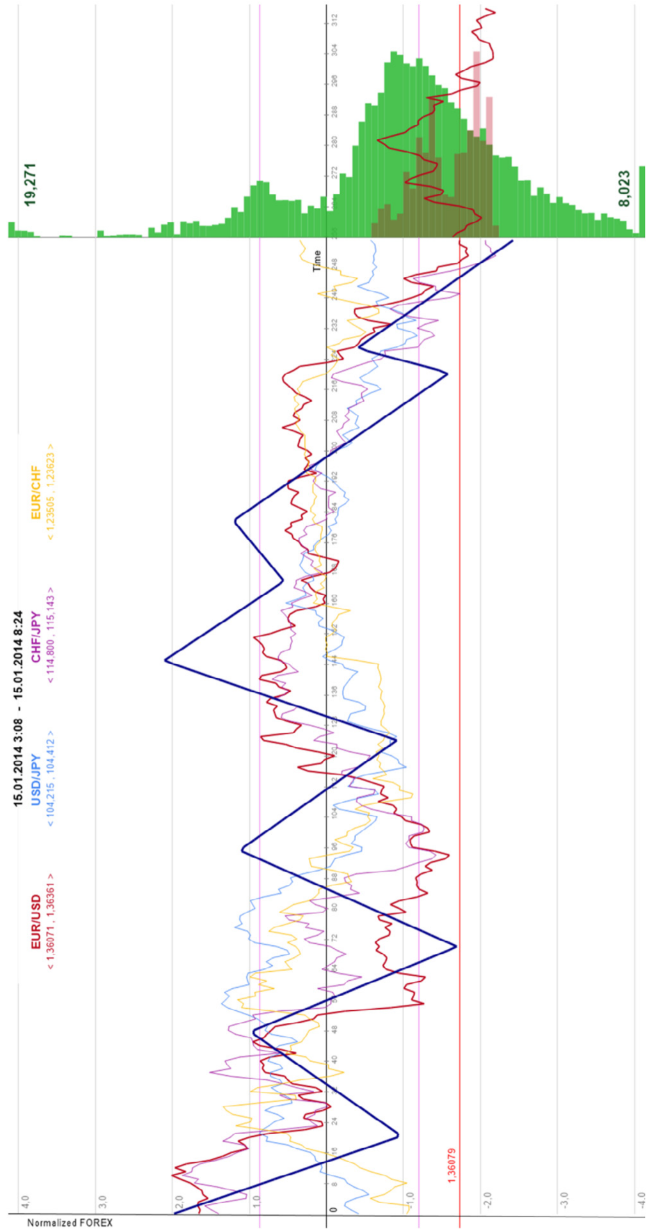

Fig. 7. Prediction of the second neural network.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Parameters of the used neural networks.

	Prediction with EW	Prediction without EW
Size of the training set for the 2nd NN	30000	30000
Size of the training set for the 2nd NN	300000	300000
Time period	2014–2020 (one minute intervals)	2014–2020 (one minute intervals)
1st NN topology	30–30–30	–
2nd NN topology	120–120–100–100	120–120–100–100
Training vectors selection	Based on similarities to EW higher than 90%	Random

6. Used metrics

Measuring the prediction accuracy (error respectively) is not an easy task since we cannot use any universal indicator. It is only based on the performed experiments that we are able to determine which key indicator is best for the solved task. In the experimental study, we will determine the accuracy of the proposed prediction model according to the following metrics, which are usually used for these purposes (Gentle, 2009). Let $y = (y_1, \ldots, y_T)$ be a time series, where T is its length and $\hat{y} = \left(\hat{y}_1, \ldots, \hat{y}_T\right)$ are its predicted values, which are expressed in the same units as the original data.

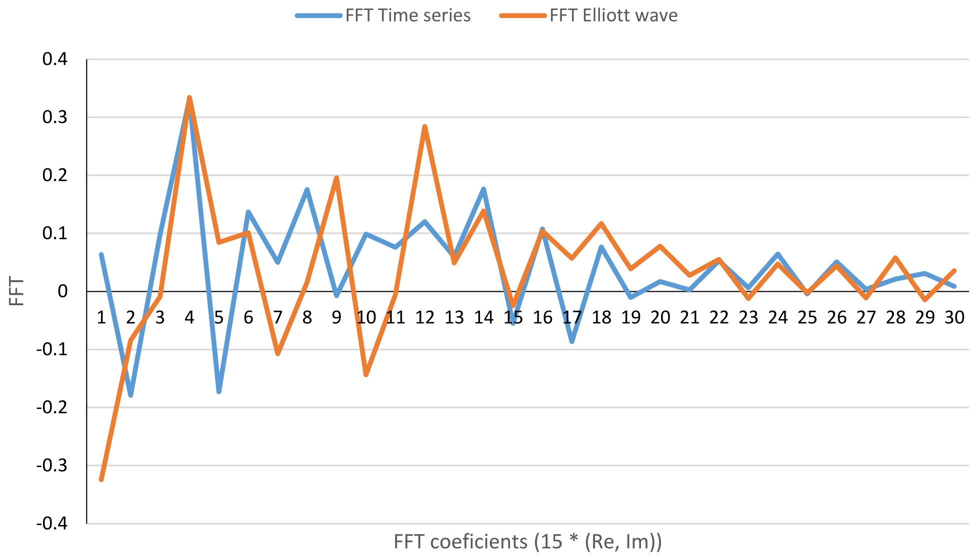

Fig. 8. FFT time series and an Elliott waves from Fig. 7.

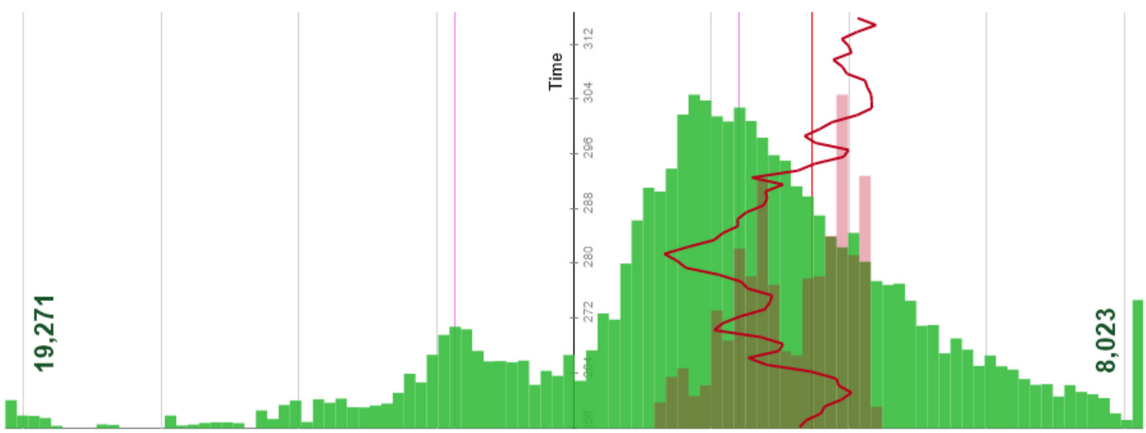

Fig. 9. Detail of Fig. 7.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Parameters of the used trading systems.

	Trading system with EW	Trading system without EW
Initial strategy	Similarities to EW higher than 90%	Random
Stop Loss	0.0005	0.0005
Take Profit	0.0005	0.0005
Striking difference	5	5
Money Management	Trade termination after max. 60 min independent of profit or loss.	Trade termination after max. 60 min independent of profit or loss.

- Mean absolute error (*MAE*) is expressed by the mean absolute error (12).

$$MAE = \frac{\sum_{t=1}^{T} \left| y_t - \hat{y}_t \right|}{T} \tag{12}$$

- Mean Square Error (*MSE*) expresses the prediction accuracy using mean square values of the differences between the predicted and real value (13),

$$MSE = \frac{1}{T} \sum_{t=1}^{T} \left(y_t - \hat{y}_t \right)^2 \tag{13}$$

where max represents the maximum value that a graphical pixel can acquire.

- Normalized Correlation Coefficient (NCC, $\langle -1, 1 \rangle$) is the cosine of the angle between two vectors (14).

$$NCC = \frac{y \cdot \hat{y}}{|y| \left| \hat{y} \right|} = \frac{\sum_{t=1}^{T} y_t \cdot \hat{y}_t}{\sqrt{\sum_{t=1}^{T} y_t^2} \cdot \sqrt{\sum_{t=1}^{T} \hat{y}_t^2}} \tag{14}$$

- The root-mean-square deviation (*RMSE*) represents the square root of the second sample moment of the differences between the predicted values and observed values or the quadratic mean of these differences (15).

$$RMSE = \sqrt{MSE} \tag{15}$$

The prediction accuracy of the proposed method was assessed using selected metrics. The results are stated in Table 4. *MSE*, *RMSE*,

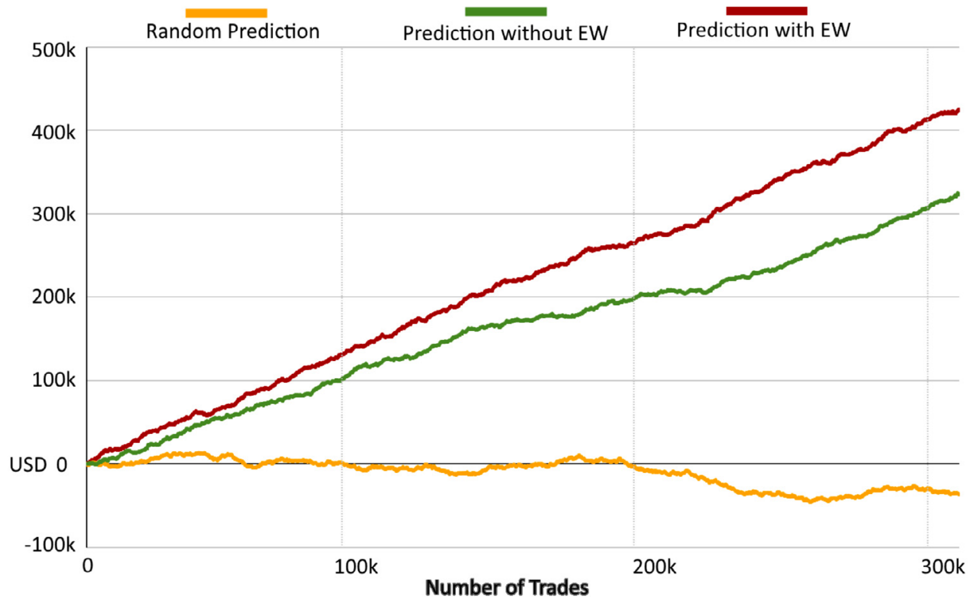

Fig. 10. Trading results.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

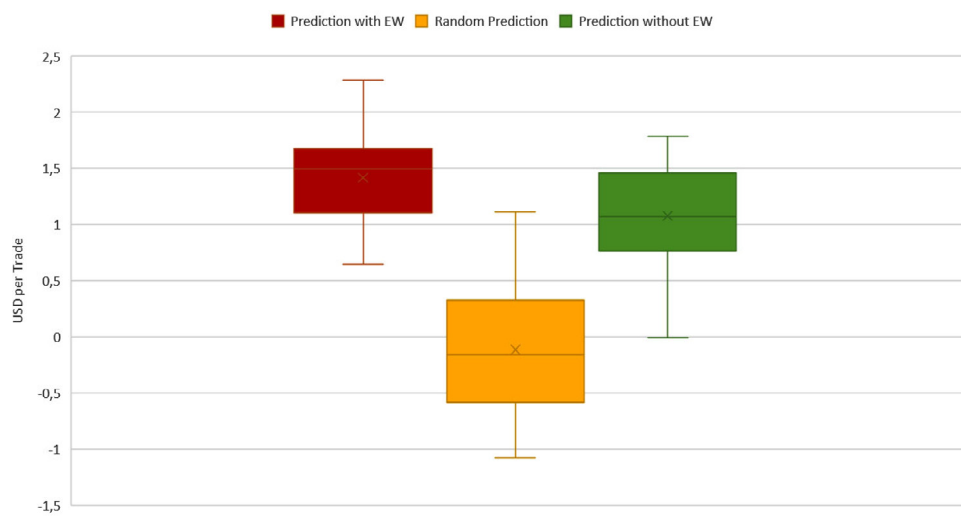

Fig. 11. Trading results.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and *MAE* in % were calculated according to formulas (16), (17), and (18).

$$MSE\ (\%) = 100 \cdot (1 - MSE) \quad (16)$$

$$RMSE\ (\%) = 100 \cdot (1 - RMSE) \quad (17)$$

$$MAE\ (\%) = 100 \cdot (1 - MAE) \quad (18)$$

NCC in % was calculated according to formula (19).

$$NCC\ (\%) = 50 \cdot (1 + NCC) \quad (19)$$

The average prediction accuracy of the proposed method using selected metrics is provided in Table 4. The average prediction accuracy of the proposed method in % is 77%.

Table 4
Average prediction accuracy of the proposed method using selected metrics.

MSE	*MSE* (%)	*RMSE*	*RMSE* (%)	*MAE*	*MAE* (%)	*NCC*	*NCC* (%)
0.11	89	0.32	67	0.22	78	0.53	76

7. Comparison with other academic works

Concerning accuracy, our achieved experimental outputs are compared with other methods published in academic works; Table 5. This table provides average published values of the performed experiments. The accuracy ranges between 50%–72% in most cases. As systems in the cited works require different approaches, they are not mutually compared under the same experimental conditions. The authors of such works present the achieved results and they achieved better than random results. According to Garcke, Gerstner, and Griebel (2012), results over 55% are generally considered worth reporting.

8. Conclusion

Financial markets prediction is a complex task. This article aimed at using real examples to prove the benefits of the Elliott Wave theory in trading simulation in the environment of financial markets prediction. In addition, next objective was to present

Table 5
Comparison of the proposed approach with other academic works.

Authors	Used method	Metrics	Accuracy rate (%)
Caginalp and Laurent (1998)	Statistic method	% of correct predictions	67
Lee and Jo (1999)	Expert system	% of correct predictions	72
Zhai, Hsu, and Halgamuge (2007)	Support Vector Machine	% of correct predictions	70
Philip, Taofiki, and Bidemi (2011)	Multilayer Perceptron	*MSE*	70
Tiong, Ngo, and Lee (2013)	Artificial Neural Networks	% of correct predictions	59
Volna et al. (2013)	Elliott wave Artificial Neural Networks	% of correct predictions	61
Tiong, Ngo, and Lee (2016)	Artificial Neural Networks Dynamic Time Warping	% of correct predictions	71
Ow, Ngo, and Lee (2016)	Multilayer Perceptron Dynamic Time Warping algorithms	% of correct predictions	72
Septiawan, Afiahayati, and Dewa (2017)	Genetic Algorithm Multiple Linear Regression	MAPD	72
Özorhan, Toroslu, and Şehitoğlu (2019)	Zig Zag Indicator Clustering Support Vector Machine	F-score	65
The proposed approach	Elliott wave Fast Fourier Transform Artificial Neural Networks	Average of *MSE*, *RMSE*, *MAE*, *NCC*	**77**

a real financial profit on a sufficiently large test samples when using the proposed methodology. A mistake of many prediction algorithms is that they predict only one development. However, practice shows that it is rather highly essential to determine the probability of either rising or falling trend at each prediction point. That was the reason to propose an innovative and unconventional approach based on suitable representation of the input data as well a robust output indicator. The whole apparatus works with the term histogram, which provides us with important information on the probability of a rising or falling trend of the predicted time series. An essential component of the proposed methodology is representation of the time development using FFT coefficients. It successfully minimizes the pattern offset problem, which is problematic in traditional feedforward neural network. At the end of the experimental part, we prove that the usage of the EW apparatus brings a significant improvement of the trading results, when the successfulness of the presented trading system achieves 77% on average. The whole work also suggests the possibility of forecasting in different time frames, because the representation of the time series by FFT coefficients is inherently independent of the time scale and also sufficiently robust to significant and unexpected market fluctuations represented by high values of AC coefficients, especially at high frequencies, which, however, do not enter the forecasting process.

Our future research will be oriented on extending the prediction methodology with other variants of configuration of the key system parameters, it primarily concerns the following areas:

- Prediction over another selected currency pair.
- Prediction in a group of an arbitrary number of currency pairs.
- Prediction over an optional length of the time widow.
- Optimization of parameters of the proposed model (degree of similarity with EW, value of the striking difference of the histogram count, stop loss, and take profit) depending on the trading system.
- Incorporation of trading charges into the trading system.
- Verification of the trading model in real trading environment.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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