8. Comparison of Forex Market Forecasting Tools Based on Evolino Ensemble and Technical Analysis Indicators

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Abstract

Financial markets are an important mechanism for allocating funds to the economy. Traders in finance markets use different strategies to increase their probability of success, and artificial intelligence is already often integrated into the investor support system. The purpose of this article is to compare the possibilities of different trading strategies to detect and predict exchange rate changes. Our model, based on an Evolino ensemble, provides two histograms based on high and low data. Probability estimation, the rejection of unlikely values, is the basis of these strategies, in which two known indicators are compared with strategies based on an Evolino ensemble prediction. Bollinger bands and Ichimoku Kinko Hyo indicators were selected because their lines determine the extreme points of fluctuation regarding exchange rates. Our findings indicate that high and low distributions received by an Evolino ensemble allow the investor to increase the probability of success and can be successfully used to robotize trading in the currency market or to develop new fintech services for investors.

Keywords: Bollinger bands, Ichimoku Kinko Hyo, Evolino, prediction, extreme values, high-low strategy

JEL Classification: G15, G17

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1. Introduction

A well-functioning financial market is the basis for a good strong economy. This has become especially evident during the COVID-19 pandemic, following the sudden need to redistribute huge financial flows. With the advent of the internet, financial markets have become accessible not only to large investors but also to individual investors. In financial markets, it is often the case that a seller who holds securities and lacks funds for operating activities solicits a buyer who currently has available funds. A new phenomenon has emerged—speculation. Rapidly changing technologies have been applied to financial market forecasting, investor support systems are being developed, and the first trading robots have appeared. Fintech start-ups are creating new services and opportunities for investors and speculators, which is making financial markets even faster and more efficient. The aim of our study is to compare seven strategies based on different forecasting paradigms and their ability to foresee financial market prices.

Discussions often arise that perhaps the financial market is not predictable. Rossi (2013) analyses different research studies, for example, stating that the predictability of the exchange market 'depends on the choice of predictor, forecast horizon, sample period, model, and forecast evaluation method'. Another author (Patel, 2010) argues that trading is a probability game and investors want to have a trading system to help increase the probability of success. The paradigm that the future is a regular result of past events is associated with mathematical cause-and-effect models, equations, and systems of equations. In the stock market, this can be applied using fundamental analysis; the foreign exchange market tries to find equations where the exchange rate is linked to macroeconomic indicators. Sinha and Kovur (2014) investigate cross-correlations of different exchange rates, and Saman (2015) examines the interaction between stock market instruments and exchange rates. Iraola and Santos (2017) connect indicators for innovation and technological progress with the main determinants of asset price volatility. Connections between the exchange rate and macroeconomic determinants such as inflation volatility, interest rates, and trade openness; and the import, producer, and consumer price indices have been investigated by Phuc and Duc (2019). Giannellis and Koukouritakis (2019) find a nonlinear regression relationship between the exchange rate, interest rate, and the price of gold using the two-regime Panel Smooth Transition Regression model with a monotonic transition function.

The second paradigm of forecasting considers the future as a logical continuation of the past. An appropriate prognosis in this case is determined by applying a time series. Prediction based on trend analysis is one of the most popular methods among investors. Strategies based on moving average (MA) (Metghalchi, Marucci & Chang, 2012), autoregressive moving average (ARMA) (Yonghong *et al*. 2015), and vector autoregressive moving average (VARMA) (Zhang, Dufour & Galbraith, 2015) have been investigated and proposed for investors. Panopoulou and Souropanis (2019) suggest using a combined forecast from technical and macroeconomic indicators to forecast exchange rates. This strategy significantly improves the accuracy and stability of the exchange rate forecast.

The third paradigm of forecasting declares that the future is the distribution of possibilities. Here, a prognosis is determined using complex probabilistic models. Some events are more likely than others, so the aim is to draw certain boundaries and rule out events that are unlikely. Lozza, Angelelli and Toninelli (2011) have proposed a comparison of portfolio selection strategies that uses market stochastic bounds. Horst *et al.* (2012) define a class of stochastic volatility models that uses opening and closing prices along with the minimum and maximum prices within a trading period to infer the dynamics underlying the volatility process of asset pricing. Corwin and Schultz (2012) use high and low daily data for developing a bid-ask spread estimator. Caporin *et al*. (2013) propose a model using high and low prices for prediction. This model aims to measure volatility by using two fundamental patterns of high and low prices thought their cointegration and long memory. Mallqui and Fernandes (2019) present a forecasting strategy to predict the price direction and maximum, minimum and closing prices of Bitcoin.

One indicator based on a definition of extreme values of the exchange rate is Bollinger bands. John Bollinger started developing this indicator in the early 1980s, and it became a popular trading tool (Bollinger, 2014), which can be used to measure the ‘highness’ or ‘lowness’ of a price relative to previous trades. Fang *et al*. (2014) have researched problems regarding the Bollinger bands trading strategy and reasons why the bands largely lost their predictive ability in major stock markets. A finance market forecasting tool using Bollinger bands and GARCH regression method is proposed in a study by Chen, Chen, and Chuang (2014). Researchers Hmood and Rilling (2013) and Itani *et al*. (2014) have both been inspired to develop new indicators for Bollinger bands. Prasetijo *et al*. (2017) combine two technical indicators, Bollinger bands and parabolic SAR, for a *buy* and *sell* signals detection.

Some trading forecasts also have been based on artificial intelligence (Paluch & Jackowska-Strumillo, 2014; Wang, Yu & Cheung, 2014; Vargas *et al*., 2018). For example, the Ichimoku Kinko Hyo indicator is a combination of different forecasts to distinguish expected currency prices from less likely ones. This indicator’s trading system was built on the idea that the exchange rate can be at a state of equilibrium (consolidation) or out of equilibrium (trending) (Patel, 2010). Ichimoku Kinko Hyo was discovered by Goichi Hosada in 1948; it is now popular in decision-making and is used together with sentiment analysis (Wang & Zychowicz, 2013) and in the creation of trading robots (Stanislav, 2015). The forecast as a distribution does not provide a very accurate numerical answer, but the investor or speculator does not need one. The direction of the price change is more important for the investor, who needs to make a decision to buy or sell a certain financial instrument. The question is how to establish a forecast distribution, which is not a new element, but has been used previously to forecast interest rates (Chaudhuri *et al*., 2016), retail sales (Kolassa, 2016), the crude oil market (Lyu *et al*., 2017), the asset returns distributions of financial market (Dhesy *et al*., 2019), andelectricity prices (Uniejewski *et al*., 2019).

In times of uncertainty, the stochastic view is more useful for prediction. Trading is a probabilistic process and the distribution of expected values best reflects trading opportunities. For the prediction of nonlinear financial time series, a neural network was used to obtain a distribution of predictions (Mohapatra *et al*., 2019). Chen and Hao’s (2020) model differs from trend-based models in that they use a weighted four-class classification algorithm and this makes it possible to predict the turning points of the price change in the future.

A forecast distribution can be obtained using a particular set of forecasting tools, where forecasts are provided by many identical or different prediction models. The result is a histogram, which gives the probabilities of certain values in the future. Artificial intelligence is convenient for obtaining a combined forecast or forecast distribution because a wide variety of architectures can be used (Di Persio & Honchar, 2016). As Zhong *et al.* (2019) prove, the use of the ensemble for forecasting is significantly more reliable and more informative. Forecasting is but one very important stage in an investor support system. Chiang *et al.* (2016) suggest illustrating how traders can expect success using a multistep decision support system model. Naranjo and Santos (2019) propose a fuzzy recommendation system based on a buy-and-hold investment strategy, demonstrating that the proposed multistep forecasting tool for investors is profitable, presents high stability, and could be a good support system. Rundo *et al.* (2019) describe an automatic trading algorithm which can be used like a support system and an ad-hoc algorithmic robot able to automatically trade in the finance market. Investor support systems can be seamlessly integrated into mobile applications and can become a daily trading tool, a great idea for a new fintech company.

The aim of our paper is to compare Bollinger bands and Ichimoku Kinko Hyo indicators with our support prediction system based on artificial intelligence and prove their ability to predict extreme values. We substantiate that our support predictions system based on an Evolino ensemble can recognise reversal points in the financial market. The rest of the article is presented as follows: Section 2 substantiates the choice of trade indicators and explains their operation, as well as presenting the support system developed for the investor based on the Evolino ensemble; Section 3 outlines the basic rules of a trading strategy; Section 4 analyses the results of a real-time trading study; and Section 5 discusses conclusions and limitations.

2. Selected Trading Indicators and Forecasting Tool Based on Evolino Ensemble

Opening and closing prices are not extreme in the exchange rate time series line, they just divide the line into equal time intervals. The highest and lowest daily prices are the daily extremes of the timeline, but their time in the period is variable. The exchange rate changes direction at extreme points. Therefore, extreme values are specific to trading in the currency market. The difference between *high* and *low* prices is always greater than the difference between *open* and *close*, so we can expect more effective daily trading. Important terms for this study are outlined below.

Bollinger bands are a well-known tool for technical analysis, invented by John Bollinger in 1980. Bollinger bands are tools of technical analysis, which seek to predict daily reversals of the finance market. This indicator defines the area of the price of a financial instrument with a higher probability. Bollinger bands consist of three lines:

- a moving average of N periods;
- an upper band two standard deviations above the moving average; and
- a lower band two standard deviations below the moving average.

The purpose of Bollinger bands is to provide a relative definition of *high* and *low*. By definition, prices are *high* at the upper band and *low* at the lower band. Bollinger bands, like other technical indicators of a similar type (Donchian channels, Keltner channels) seek to define the boundaries between less and more probable values. By rejecting less probable values, trading strategies that use Bollinger lines for forecasting can be developed. Observing historical data, it can be estimated that the probability that a price will go beyond the top or bottom line is very low. Usually in those places, a change in the price of a financial instrument switches direction.

Ichimoku Kinko Hyo (IKH) is an indicator that determines the state of the exchange rate: trending or reversal. The trading platform (Oanda, 2016) describes the five main lines:

Conversion Line = (Highest High + Lowest Low) / 2, for the past x periods;
Base Line = (Highest High + Lowest Low) / 2, for the past y periods;
Lagging Span = Today's closing price plotted y periods behind;
Senkou Span A = (Tenkan-Sen + Kijun-Sen) / 2, plotted y periods ahead;
Senkou Span B = (Highest High + Lowest Low) / 2, for the past z periods, plotted y periods ahead.
IKH indicator lines and clouds have also broken down the full range of possible future prices into less and more likely areas. We are interested in the reversal point, which is determined by the crossing of the Tenkan-Sen and Kijun-Sen lines. Trading with Ichimoku Kinko Hyo is simple: two main lines determine the signals of *buy* and *sell*, and the trend direction. Other lines determine the strength of the signal. The Kumo cloud measures volatility.

Evolino ensemble is based on artificial intelligence. Wierstra, Gomez and Schmidhuber (2005) have proposed this as a new class of artificial intelligence algorithms, or Evolino (Evolution of recurrent systems with optimal linear output). The algorithm was tested for the Maclay-Glass process but was not used in financial markets. It was adapted for predicting the exchange market in such a way that the network parameters (number of iterations, number of neurons, orthogonality of inputs) are selected, and this allows for a more accurate prediction (Rutkauskas, Maknickiene & Maknickas, 2010).

Historical data of the exchange rate, what we wanted to predict in this study, was used for the first input. Historical data of the commodity market was instituted as the second input. Two thousand points of daily trading *high* and *low* prices were evaluated on a daily basis to add new data. For our experiment we selected closest to orthogonal exchange rates (Roll, 1980; Maknickiene, 2014). The use of the mathematical expression of orthogonality can be understood as independence because currency fluctuations are influenced by globalization, the neighbourhood of countries, or belonging to an economic community as the European Union. As measures for assessment we use the following currencies: GBP/AUD is Great Britain pounds and Australian dollars, NZD/CAD is New Zealand dollars and Canadian dollars, EUR/JPY is European Union Euro and Japanese Yen, USD/CHF is US dollars and Swiss Francs. After many tests and comparisons with other indicators prices of gold in US dollars was selected for the second input.

The distribution of expected values was achieved by using an Evolino ensemble from 176 recurrent neural networks predicting simultaneously but using different historical data. The Evolino ensemble acts as an expert system where each agent submits their own forecast. The prediction model (Maknickiene & Maknickas, 2016) is shown in Figure 1. The model can use a different number of predictors, and the forecasting process consists of the following steps:

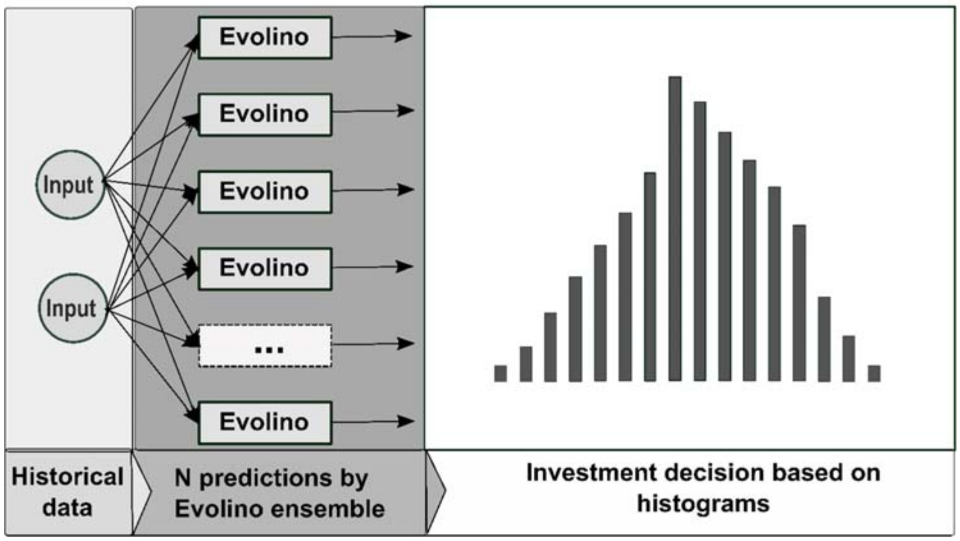
Data preparation. Two years of historical exchange rate data serves as the first input. After many attempts, XAUUSD (gold price in US dollars) was chosen as the RNN supervisor and two years historical data were prepared for the second input. The prepared historical database can be used in the next step.

Prediction. We can choose the Evolino RNN number in the ensemble, but then the predictions may take a very long time and the accuracy does not increase linearly. Each prediction is made twice, with maximal and minimal historical data. At the end of this step, we have two distributions of expected values with all parameters of distribution—mean, median, mode, skewness, kurtosis, and shape.

Investment decision. Trading decisions are made by analysing the composition of high and low histograms and its parameters, obtained by predicting with the Evolino ensemble.

Figure 1

Prediction Model Based on Evolino RNN



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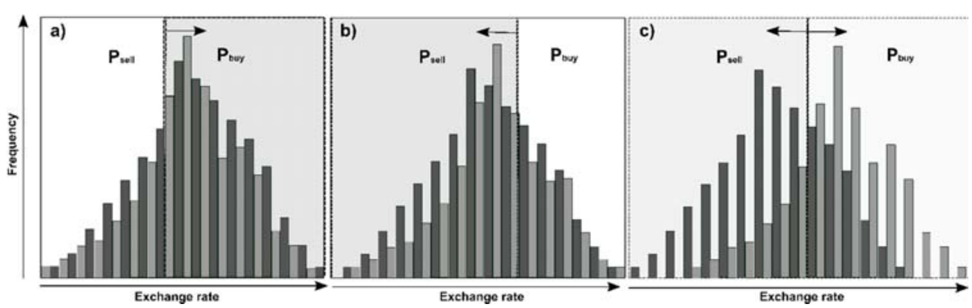
Prediction is made from different data—*high* and *low* for all four exchange rates. Decision-making depends on the composition of *high* and *low* histograms and the last known value, which divides the histograms into two areas: to the left is the fall in price and to the right is growth. Our *high-low* method is presented in another paper (Stankevičienė, Maknickiene & Maknickas, 2014). Three cases of predictions with different decisions are shown in Figure 2.

Figure 2

Cases of Predictions: a) Decision *buy* P_{buy} >P_{sell}; b) Decision *sell* P_{buy} <P_{sell}; c) Decision Is Risky P_{buy} Is Approximately Equal to P_{sell}



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The left image (a) depicts a *sell* signal, because the most part of both histograms—*high* and *low* —are to the left of the last known value (dotted line). In cases when both histograms are to the right of the last known value, we have a *buy* signal. In the right image (b), histograms are in different sizes from the last known value, and the decision is so risky that the investor must wait for better signals.

3. Real Time Trading Strategies

Successful trading or speculation in financial markets requires investor discipline not to give in to emotions, and this is achieved by developing and testing trading strategies in real time. Our research is based on modern portfolio theory, so two methods of portfolio formation will be used:

Conservative. Dividing the investment funds equally for each exchange rate. For this strategy the main modes of distribution can play a role in defining *take profit*, and the portfolio of exchange rates is constructed of equal parts of investment funds.

Moderate. Optimizing for maximum return. This strategy is also *take profit*, but asset allocation is distributed in proportion to the likely profit.

The selected maximum and minimum data is different from opening and close data and allows for the prediction of a change in the exchange rate price trend. Decision-making rules are determined by the characteristics of the chosen indicator or artificial intelligence model. The rules serve as a rigorous basis for trading strategy and allow for comparisons between different options for risk, profitability, and the ability to recognize extreme values. We consider that Bollinger bands define daily exchange rate conversions and, on these grounds, we form trading rules. According to the *buy* rule:

$$\begin{gathered}\textbf{If } a_{t-1} < b_{t-1\,low}\text{: } \textbf{\textit{buy}}\\ \textbf{while } a < b\text{: } \textbf{\textit{wait}}\\ \textbf{If } a_t = b_{t\ high}\text{: } \textbf{\textit{sell}},\end{gathered} \tag{1}$$

where: a_{t-1} close data, a_t – real-time data, $b_{t-1\,low}$ – lower Bollinger band at time *t*; $b_{t\ high}$ – upper Bollinger band at time *t*.

Sell rule:

$$\begin{gathered}\textbf{If } a_{t-1} > b_{t-1high}\text{: } \textbf{\textit{sell}}\\ \textbf{while } a > b\text{: } \textbf{wait}\\ \textbf{If } a_t = b_{tlow}\text{: } \textbf{\textit{sell}},\end{gathered} \tag{2}$$

a trading decision is made every selected period of time when the market is closing for four exchange rates: GBP/AUD, NZD/CAD, EUR/JPY, and USD/CHF.

Ichimoku Kinko Hyo trading *buy* rule:

$$\begin{gathered}\textbf{If } b > r\text{: } \textbf{\textit{buy}}\\ \textbf{while } b < r\text{: } \textbf{\textit{wait}}\\ \textbf{If } b = r\text{: } \textbf{\textit{sell}},\end{gathered} \tag{3}$$

where: b is last point of the Kijun-Sen line, r – last point of Tanken-Sen line.

Sell rule:

$$\begin{gathered}\textbf{If } b < r\text{: } \textbf{\textit{sell}}\\ \textbf{while } b < r\text{: } \textbf{wait}\\ \textbf{If } b = r\text{: } \textbf{\textit{sell}},\end{gathered} \tag{4}$$

trading by four selected exchange rates is made every selected period of time when the market is closing.

Evolino ensemble predictions are two stochastically informative distributions of expected values—*high* and *low*. Trading decisions depend on the last known value a_{t-1} and the composition of histograms (Fig. 2).

The calculated probability of profit, when the decision is *buy:*

$$p_{pbuy} = \frac{p_{phigh}+p_{plow}}{2}, \tag{5}$$

and the probability of loss:

$$p_{lbuy} = \frac{p_{lhigh}+p_{llow}}{2} = 1 - p_{pbuy}. \tag{6}$$

When the decision is *sell*, the probability p_{psell} is calculated by analogy. The trading rule of this method is as follows:

If $p_{pbuy} > p_{psell}$: **buy**
else: ***sell***. (7)

If p_{pbuy} is approximately equal to p_{psell}, trading is so risky that the investor needs to wait for clearer predictions. A standard deviation of more than 20% of the mode value shows the riskiness of trading. Rule 7 is used for decision-making. The trading decision for all strategies is made by selecting a period of time when the market is closed for four exchange rates: GBP/AUD, NZD/CAD, EUR/JPY, and USD/CHF.

The study involves real-time trading, comparing two technical indicators on the demo platform—Bollinger Bands and Ichimoku Kinko Hyo—with the Evolino Recurrence Neural Network Ensemble, whose prediction is a distribution. A conservative portfolio allows us to evaluate a less risky trading strategy while moderately showing how the strategy works when it comes to maximizing profits.

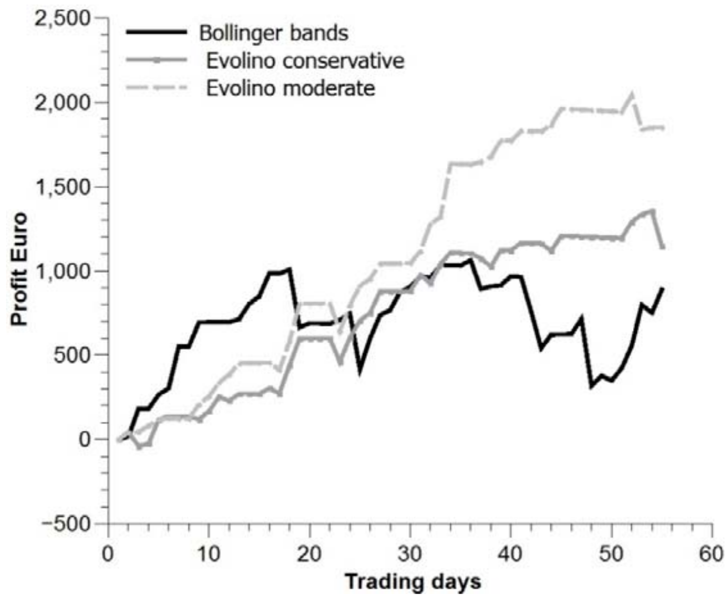
4. Comparison of Exchange Market Predictions Based on Extreme Data

Our investor support system based on an Evolino ensemble was compared with known indicators, which have similar characteristics, to identify changes in the market points and extreme values.

The validation of our model and strategies was made by trading online using the demo platform Oanda. Comparison of the Bollinger band indicator with an Evolino ensemble-based prediction was made by daily trading. Three marketing strategies were carried out by using the simulation market trade in real-time during the same period. Bollinger's bands-based strategy uses rules 1 and 2. Evolino-based strategies use rule 7. The profitability of these strategies is shown in Figure 3. The results show that the trading strategy based on Bollinger bands is very successful in the period from 1 to 17 and from 26 to 36 trading days. But there are periods with strings of losses—from 18 to 25 and from 37 to 49 trading days. Bollinger bands are a good enough indicator when exchange rate fluctuations have a clear trend. Trading when the price of the exchange rate does not have a clear trend requires including Bollinger bands in the combination of forecasts with other indicators. The *conservative* and *moderate* Evolino strategies do not have periods of losses. The profitability grows evenly there. The *moderate* strategy is more profitable than the *conservative*.

Figure 3

Comparison of Trading Results in an Imitated Market in Real Time



Source: Created by authors.

The purpose of the Bollinger Bands indicator is to illustrate signals that would determine the reversal points of exchange rate fluctuations. By definition, prices are *high* at the upper band and *low* at the lower band. Comparison of Bollinger bands and the recognition of *high* and *low* points in the exchange market using our support predictions system based on artificial intelligence is presented in Table 1. The profitability and profit per trade of the support prediction system is greater than that of the strategy based on Bollinger bands. The maximal profit and maximal loss show that trading with the Bollinger bands strategy is riskier, and minimal risk was obtained just with the conservative strategy.

Table 1

Comparison of Trading Strategies

Factor	Bollinger	Evolino conservative	Evolino moderate
period (trading days)	55	55	55
Profitability (%)	0.9	1.2	1.9
Profitability (Euro)	888.81	1145.6	1848.53
Profit/trade	16.16	20.83	33.61
max profit (EUR)	243.21	146.32	212.15
max lost (EUR)	-487.24	-242.91	-262.67
MAE	10.9	9.1	6.8

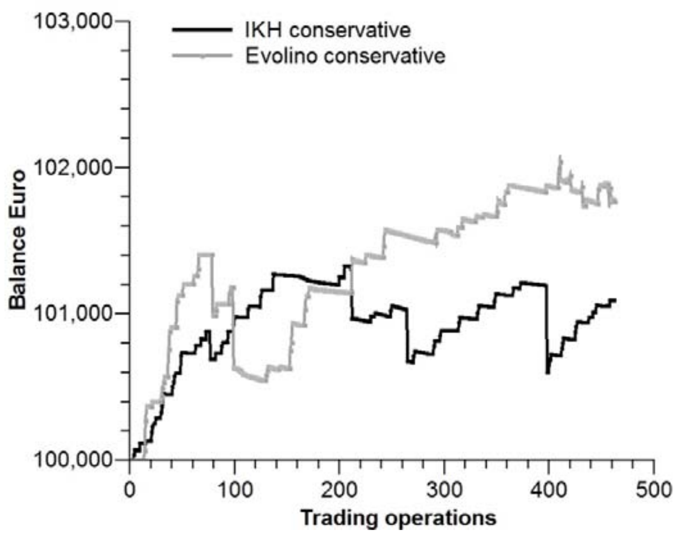
Source: Created by authors.

The comparison predicted *high* and *low* bands and real daily extreme values, measured as mean absolute error (MAE), show that the modes of *high* or *low* distributions are close to real *high* or *low* values.

Comparison of the Ichimoku Kinko Hyo indicator and an Evolino ensemble-based prediction is made by weekly trading. In an online demo platform, we created four portfolios: IKH conservative, IKH moderate, Evolino conservative, and Evolino moderate. Trading decisions were made by using rules 3 and 4 for IKH and rule 7 for the Evolino ensemble. The trading was carried out with four exchange rates: GBP/AUD, NZD/CAD, EUR/JPY, and USD/CHF. The comparison of conservative strategies is presented in Figure 4. The conservative strategy deals investment funds in equal parts for each exchange rate in the portfolio.

Figure 4

Results of Trading in an Imitated Market in Real Time



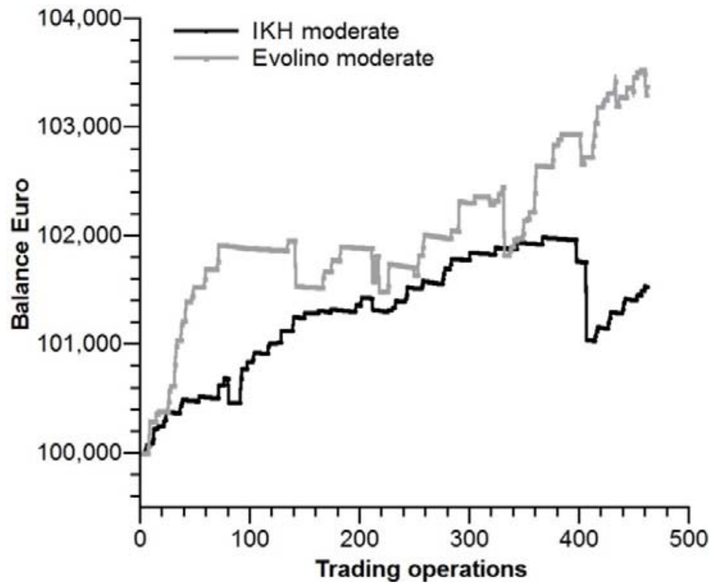
Source: Created by authors.

Trading by IKH has six successful periods and four major losses. Trading by the Evolino ensemble is more successful in almost all periods of trading with only two big losses. The IKH indicator does not determine the points of *take profit* and *stop loss*. The Evolino ensemble-based support system for investors determines *take profit* as the main mode nearest to the last known value. *Stop loss* is determined as the second mode on the other side of the last known value, so there the losses are less.

Comparison of trading by moderate strategies is shown in Figure 5. The portfolio for the moderate strategy is constructed in proportion to the likely profit, so the moderate strategy can eliminate risky predicted exchange rates from the portfolio. Both results using the moderate strategy are better than those using a conservative approach.

Figure 5

Results of Trading in an Imitated Market in Real Time



Source: Created by authors.

A comparison of conservative and moderate trading strategies by using the IKH indicator and the Evolino ensemble is presented in Table 2. The profitability of trading by using a moderate strategy is more than using a conservative approach because portfolio optimization can eliminate risky exchange rates. Profitability and profit per trade using Evolino is more than profitability and profit per trade using the IKH indicator. Maximal profit depends on prediction by the Evolino ensemble, but it is not determined by the IKH lines. Maximal loss depends on the Evolino predictions, but it does not depend on the IKH lines. The MAE depends only on the loss because *take profit* is determined at the point of prediction.

Table 2

Comparison of Trading Strategies

Factor\strategy	IKH conservative	IKH moderate	Evolino conservative	Evolino moderate
Period (weeks)	32	32	32	32
Profitability (%)	1.1	1.5	1.8	3.4
Profitability (Euro)	1,091.39	1,530.27	1,773.41	3,372.59
Profit/trade	15.37	21.86	26.86	41.13
Max profit (EUR)	118.33	218.81	232.75	274.32
Max lost (EUR)	-356.24	-219.72	-128.74	-275.43
MAE	14.25	8.09	8.94	16.84

Source: Created by authors.

The study did not seek to predict a particular point in the future because we hold the position that forecasting tools based on probabilities better reflect the decision-making in uncertainty. Therefore, prediction methods that define a set of more probable values were chosen. In this set, we sought to find certain boundaries that allow us to recognize the possibility of a change in the direction of the exchange rate. Indicators of very different natures compare in real-time trading according to the same property: whether they allow the recognition of extreme values in exchange rate fluctuations. Testing selected strategies of trading in the exchange market confirmed that our support prediction system based on artificial intelligence can outperform the prediction of extreme values.

5. Conclusions

Models based on the paradigm that the future is a distribution of possibilities are probabilistic: they do not calculate the program at a single point, but estimate different possibilities for future events to occur. In the trading process this paradigm requires a proven strategy that uses certain forecasting tools, risk management tools, and rules that prevent irrational action. The selected maximum and minimum data allow for predictions of the change in the exchange rate price trend. As artificial intelligence develops and grows in popularity, it is also integrated into trade strategies, and support systems are developed on its performance. The forecasting paradigm chosen for the study is that the future is a distribution of opportunities. The selected technical indicators, BB and IKH, were compared with the Evolino neural network ensemble, whose prediction result is a distribution of expected values.

The composition of *high* and *low* distributions is stochastically informative for investors. An Evolino ensemble can predict fluctuations in the direction of exchange rates and determine the daily high and low bands. Bollinger bands are effectively used when they parallel the moving average, but they cannot accurately predict when the exchange rate does not have a strong trend. Our support prediction system can give stable predictions in the market without a strong trend. Trading strategies using the support prediction system based on an Evolino ensemble also surpassed strategies based on the Ichimoku Kinko Hyo indicator. Lines and clouds of IKH are informative and help to recognize the states of fluctuation of exchange rates, but using the *high* and *low* distributions obtained by an Evolino ensemble allows to determine trading points and produce higher profit per trade and total profit for the same market conditions. Therefore, *high* and *low* distributions received by an Evolino ensemble allows the investor to increase the probability of success.

The study has several limitations. First, the period during which the study was conducted, when financial markets were relatively calm, compared to periods of extreme anomalies. Second, the trading system was not fully automated, which may lead to some bias on the part of the researchers, although the rules created have greatly reduced this potential.

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