Investment Support System using the EVOLINO Recurrent Neural Network Ensemble

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Abstract: The chaotic and largely unpredictable conditions that prevail in exchange markets are of considerable interest to speculators because of the potential for profit. The creation and development of a support system using artificial intelligence algorithms provides new opportunities for investors in financial markets. Therefore, the authors have developed a support system that processes historical data, makes predictions using an ensemble of EVOLINO recurrent neural networks, assesses these predictions using a composition of high-low distributions, selects an orthogonal investment portfolio, and verifies the outcome on the real market. The support system requires multi-core hardware resources to allow for timely data processing using an MPI library-based parallel computation approach. A comparison of daily and weekly predictions reveals that weekly forecasts are less accurate than daily predictions, but are still accurate enough to trade successfully on the currency markets. Information obtained from the support system gives investors an advantage over uninformed market players in making investment decisions.

1 INTRODUCTION

Exchange markets are extremely dynamic, chaotic, and largely unpredictable. They are influenced by market participants, as well as by banking interventions, manipulations, geopolitical events, natural disasters, and other external events. However, the real challenge of creating a support system for speculators can be realized by artificial intelligence.

Decision making in uncertain markets requires complex solutions covering several fields of science, artificial intelligence, and investment. In the scientific field of artificial intelligence, we found a very interesting algorithm named EVOLINO (EVolution of recurrent systems with Optimal LINear Output) (Schmidhuber et al., 2005a) , (Wierstra et al., 2005). When trained using Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), (Gers et al., 2000) recurrent neural networks (RNNs) with co-evolving hidden neurons, EVOLINO can learn to predict several time series that traditional RNNs cannot. EVOLINO has been used to predict superimposed out-of-phase sine waves, certain input streams based on grammatical rules, the parity problem with display, and the Mackey–Glass time series (Schmidhuber et al., 2005b), (Schmidhuber et al., 2007), as well as in the modelling of competence as a self-organizing process (Scharnhorst and Ebeling, 2005) and robotic knot winding (Mayer et al., 2008).

Single neural networks have the qualities needed to achieve this objective, but a group of them, connected in different ways, can provide qualitatively new solutions. Ensembles of neural networks have been used to predict exchange rates (Zhang et al., 2001), in single-step-ahead and multi-step-ahead prediction problems (Assaad et al., 2008), for bankruptcy prediction and credit scoring (Tsai and Wu, 2008), wind power forecasting (Felder et al., 2010), and noisy non-linear time series (Sheng et al., 2013). The probabilities given by these ensemble predictions are used in climate change research (Collins, 2007) and probabilistic wind vector forecasting (McLean Sloughter et al., 2013).

In investment theory, most attention is focused on investment portfolio formation. The best known studies in this area were conducted by Markowitz (Markowitz, 1952), (Markowitz, 1987), (Markowitz, 2014), who proposed equations for maximizing profit and minimizing risk. The adequate portfolio (Rutkauskas, 2000) added a third component—reliability. The formation and usage of this adequate portfolio has been analysed in terms of profit stochas-

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ticity (Rutkauskas and Stankevičiene, 2003). Orthogonal portfolios were investigated in the context of a saving and investment portfolio (Roll, 1980), and the optimal orthogonal portfolio has become an important risk management tool in investment decision making processes (Asgharian and Hansson, 2005), (Asgharian, 2011).

Investment strategies based on extremal data have also been studied (Corwin and Schultz, 2012), (Caporin et al., 2013). Hence, the high and low prices in an exchange market are frequently predictable and profitable for speculation.

One of the most important measures of feature predictions is time. Short-term predictions of the future behavior of a time series, using information based only on past values, have been researched (Farmer and Sidorowich, 1987), as has the prediction of chaotic time series using artificial intelligence (Samanta, 2011), (Chen, 2014), (Fonseca and Gómez-Gil, 2014).

Our aim is to integrate knowledge of investment theory and artificial intelligence to develop a support system for speculating on the exchange markets. Information obtained from the support system must give investors an advantage in making investment decisions compared with uninformed market players. The proposed support system for speculators includes five steps: preparation of historical data, prediction by an ensemble of EVOLINO RNNs, assessment of predictions, investment portfolio formation, and verification in the market. Our research compares two portfolios based on different perspectives of the future: daily and weekly time series.

2 SUPPORT SYSTEM

Figure 1 shows a block diagram of different stages of our support system for investors in the currency market. The data include historical fluctuations in exchange rates. The prediction model provides a full set of forecasts, which is the basis for investment asset allocation over the prediction assessment and portfolio optimization. Verification in an imitation market in real time demonstrates the reliability of the support system.

2.1 Preparation of Historical Data

The selection of exchange rates for speculation in currency markets is based on the orthogonality of the portfolio. Roll (1980) formulated the conditions under which an investment portfolio solves the efficient portfolio optimization problem. An orthogonal portfolio is one which satisfies the following condition:

$$Var = \Sigma_{ij} r_{ij} \sigma_i \sigma_j = 0, \tag{1}$$

where r_{ij} is the correlation coefficient between tools i and j, σ_i is the standard deviation of tool i, and σ_j is the standard deviation of tool j.

When it is very difficult to reach $Var = 0$, we can use ε to denote the degree of closeness to orthogonality:

$$Var = \sum_{ij} r_{ij} \sigma_i \sigma_j = \varepsilon. \tag{2}$$

In our research, we use the GBP/AUD (British pounds and Australian dollars), NZD/CAD (New Zealand dollars and Canadian dollars), EUR/JPY (Euro and Japanese yen) and USD/CHF (US dollars and Swiss francs) exchange rates. The weekly exchange rates are recorded in a MySQL database on a daily basis. Additionally, we record the XAUUSD rate (gold against the US dollar). The optimal orthogonality of two "pupil and teacher" data vectors can be achieved by varying $a \geq 0$ while seeking to minimize the sum (Maknickas and Maknickiene, 2012):

$$\min \sum_{t=0}^{N-1} \eta^{t}_{XXX/YYY} \eta^{t-a}_{XAU/USD}. \tag{3}$$

The best shift value a is then recorded in the MySQL database for future usage. Note that we do not use the direct η^t_i exchange rate data (where index i denotes currency exchange rates GBP/AUD, NZD/CAD, EUR/JPY, USD/CHF), but the following rational logarithmic data of η^t_i and η^{t-1}_i:

$$l^j_t = \log(\eta^t_j / \eta^{t-1}_j). \tag{4}$$

The logarithmic scale was chosen in case of lognormal distribution of investigating data. So, a neural network will learn unified data of logarithmic rational exchange rates growth/decrease. Thus, in our case, four different shift values must be found and stored. When the best shift values have been determined, the EVOLINO RNN can begin the learning process. EVOLINO RNN learning data must be in the range $[0, 1]$, so the original data are normalized according to the maximum value in the interval $[0, T]$, i.e.

$$l^{1j}_t = l^j_t / l^j_{max}. \tag{5}$$

The data prepared in this way can be used for LSTM second-order RNN learning and validation. The predicted data should be obtained in the reverse algorithm using the same value of l^j_{max}. In the prediction stage, all learned RNN predicted exchange rate values must be multiplied by l^j_{max}. The exponent of each predicted value is calculated as follows:

$$\eta^t_j = \eta^{t-1}_j \exp(l^{1j}_t l^j_{max}), \tag{6}$$

where η^0_j is the first value in the predicted time series.

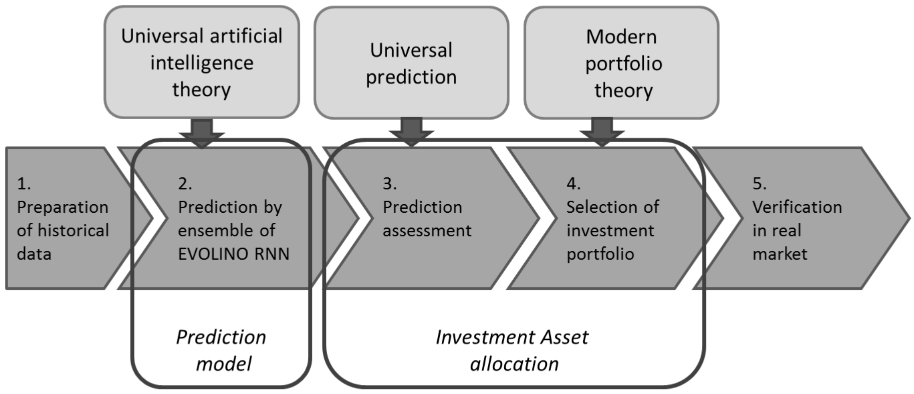

Figure 1: Diagram of support system for investors.

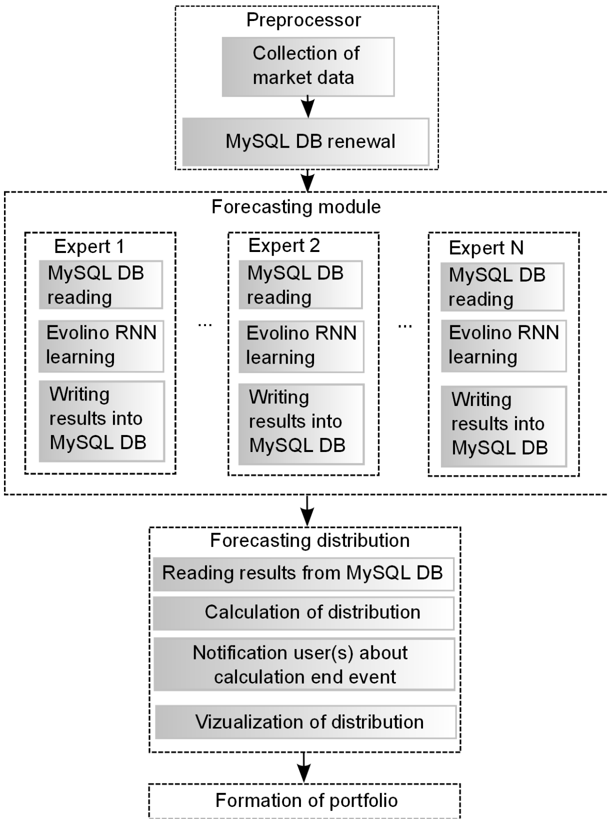

Figure 2: Diagram of prediction model.

2.2 Prediction by an Ensemble of EVOLINO RNNs

The idea of using LSTM RNNs to predict exchange rate time series is based on the formers ability to obtain qualified prediction results for the Mackey–Glass chaotic time series (Gers, 2001). This success could be explained by investigations of Siegelmann (1999), who proved that first-order RNNs could work as finite state automata if their weights were integers, as Turing machines if their weights were rational numbers, and as super Turing machines or hyper-computers if their weights were real numbers. The EVOLINO RNN is an LSTM second-order RNN, and researchers (Goudreau et al., 1994) have shown that these are strictly more powerful than first-order RNNs. Thus, if LSTM works well for the prediction of Mackey–Glass chaotic time series, it should work equally well for the prediction of chaotic exchange rate time series.

The second basic idea of artificial prediction is that we should not only predict a single point in the future, but a distribution of points. This means that there are no single fixed points in the future, but rather an infinite number of points with an appropriate probability of appearing in the future. This was taken into account by our algorithm using an ensemble of EVOLINO RNNs to obtain the predicted distribution of possible exchange rate values. When using an ensemble, we require unrealistic values to be filtered out. In this case, the first–last percentile method was used. Calculating the first and fourth percentiles allows us to remove values in this range as unrealistic.

Finally, we obtain the future single-step ahead (one week or one day in the current investigation) distribution of possible exchange rate values, and use this to make decisions about appropriate investments. This can be done because the weights are globally optimized using a genetic algorithm, and each optimization sequence gives different values for a single prediction point.

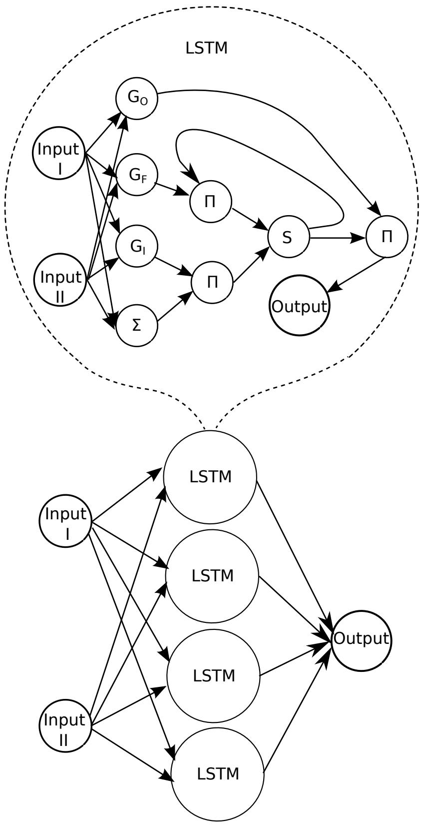

Figure 3: LSTM network with four memory cells.

The block diagram of EVOLINO recurrent neural network is shown in Figure 3. EVOLINO RNN forms LSTM network with $N = 4n$ memory cells, where N is total amount of neurons and n is amount of memory cells. The genetic evolution algorithm is applied to each quartet of memory cells separately. The cell has an internal state S together with a forget gate (G_F) that determines how much the state is attenuated at each time step. The input gate (G_I) controls access to the cell by the external inputs that are summed into the Σ unit, and the output gate (G_O) controls when and how much the cell fires. Nodes Π represent the multiplication function and the linear regression Moore-Penrose pseudo-inverse method used to compute the output circle (Schmidhuber et al., 2005a), (Schmidhuber et al., 2005b).

The EVOLINO forecasting module is presented in Figure 2. The module consists of four parts: preprocessor, forecasting, calculation of distribution and formation of portfolio. The prerocessor part colect data into MySQL data base. The forecasting part learns, validates and predicts each expert(4xLSTM neural network) in the separate thread. Finally, the obtained prediction data are using for calculation of future distribution and formation of portfolio. A detailed description of neural network ensemble learnig, validation and prediction using EVOLINO RNNs can be found in Maknickiene and Maknickas (2013). Ensembles of neural networks can take a number of hours to reach a satisfactory convergence. Selection of the optimal number in an ensemble has been investigated in earlier work (Maknickienė and Maknickas, 2013). The cycle of each predictive neural network is divided into equal intervals, and every interval is computed on a separate processor node. Hardware acceleration is achieved using eight nodes of an Intel(R) Xeon(R) CPU E5645 @ 2.40 GHz on the www.time4vps.eu cloud. An ensemble of 1008 predictive neural networks requires approximately 72 h computation time. The forecast assumes the distribution has a particular shape. At the end of this step, the support system user obtains the distribution and parameters such as the mean, median, mode, skewness, and kurtosis.

2.3 Prediction Assessment

The prediction model outputs a multi-modal distribution, and its shape provides more information for investors. The standard deviation reflects the riskiness of a decision, kurtosis indicates the dispersal of possible values, and skewness indicates the asymmetry of the decision. Second and third modes also provide information about changes in the future exchange rate value. When the historical data consist of closing values, the distribution of expected values predicts the closing exchange rate for the next period. However, close data are less informative for investors. Each investor makes a decision to *buy* the lowest data and *sell* the highest data. Thus, for the prediction assessment, we use the composition of two distributions, one of which was produced using low data, the other using high data. In real markets, decisions are made according to the exchange rate value at the moment of decision-making (Stankevičiene et al., 2014).

2.4 Selection of Investment Portfolio

Selection of investment portfolio using the composition of distributions should be made according to:

$$\begin{cases} max & \sum_{i=1}^{n} p_{pi} W_i \\ min & \sum_{i=1}^{n} p_{li} W_i, \end{cases} , \qquad (7)$$

where p_{pi} is the probability of profit, p_{li} is the probability of loss, W_i is part of the investment in exchange rate i, and n is the number of exchange rates in the portfolio.

This orthogonal optimal portfolio diversifies risk and makes investment in exchange markets profitable. Real-time verification in an imitation market allows us to evaluate the investor support system in terms of market profitability, risks, and reliability, as well as the individual characteristics of the investors speculating on the real market.

3 COMPARISON OF DAILY AND WEEKLY PREDICTIONS USING OUR SUPPORT SYSTEM FOR INVESTORS

The time interval is a very important component in chaotic processes. Predicting financial markets for short periods is slightly easier than making long term predictions. The hourly forecasts given by our support system required 16–18 h forecasting data. There are insufficient historical data to produce a long-term (e.g., monthly or annual) prognosis. The accumulated experience with daily data forecasting allows us to go one step into the future and use weekly exchange rate forecasts.

3.1 Daily Predictions

Short-term predictions were made using historical data on daily highs and lows. Trading decisions can be made using a composition of two distributions, taking into account that the close value is the last known real value. Figure 4 shows the composition of distributions for the expected GBP/AUD exchange rate. The modes of these distributions are to the left of the close value, thus the trading decision must be to *sell*. The modes of the EUR/JPY (Figure 5) and NZD/CAD (Figure 6) exchange rate high-low distributions are to the right of the close values, so the trading decision in these cases is *buy*.

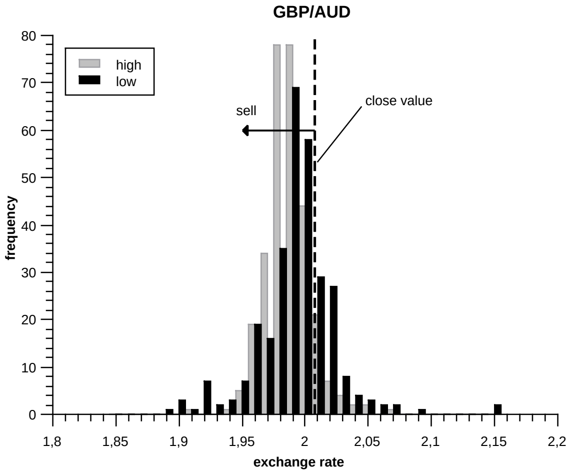

Figure 4: Composition of high-low distributions of daily GBP/AUD exchange rate predictions.

The probability of profit $P_p = 0.89$ and the probability of loss $P_l = 0.11$ in the case of the daily GBP/AUD *sell* trading decision (Figure 4). For the

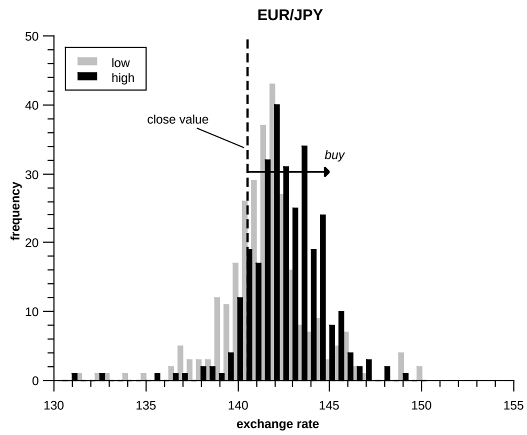

Figure 5: Composition of high-low distributions of daily EUR/JPY exchange rate predictions.

EUR/JPY *buy* trading decision, the probability of profit $P_p = 0.58$ and the probability of loss $P_l = 0.42$ (Figure 5). The probability of profit $P_p = 0.77$ and the probability of loss $P_l = 0.23$ for the daily NZD/CAD *buy* trading decision (Figure 6).

The portfolios are formed using equation (7). The calculated weights are: $W_{D,gbp/aud} = 0.53$, $W_{D,eur/jpy} = 0.11$, and $W_{D,nzd/cad} = 0.36$.

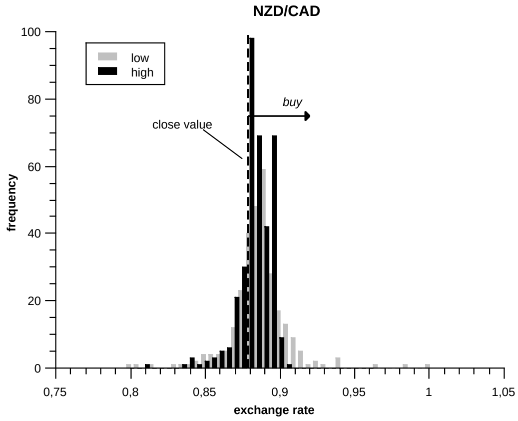

Figure 6: Composition of high-low distributions of daily NZD/CAD exchange rate predictions.

3.2 Weekly Time Period

Weekly predictions are made in the same way as daily predictions, but with weekly historical exchange rate data. Figure 7 shows the composition of weekly GBP/AUD exchange rate expected value distributions. The modes of the distributions are to the left of the close value, so the trading decision must be to *sell*. The modes for EUR/JPY (Figure 8) are on opposite sides of the close value, so *buy* or *sell* decisions are very risky. The modes of the weekly NZD/CAD (Figure 6) exchange rate high-low distributions are to the right of the close value, so the trading decision here is to *buy*. The probability of profit $P_p = 0.78$ and

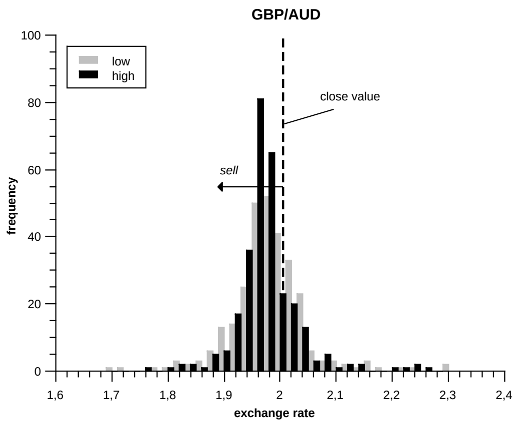

Figure 7: Composition of high-low distributions of weekly GBP/AUD exchange rate predictions.

the probability of loss $P_l = 0.22$ in the case of the weekly GBP/AUD *sell* trading decision (Figure 7). For the risky trading decision concerning the weekly EUR/JPY rates, the probability of profit is $P_p = 0.502$ and the probability of loss is $P_l = 0.498$ (Figure 8).

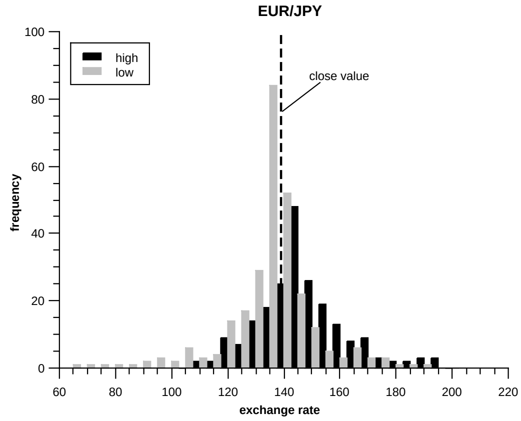

Figure 8: Composition of high-low distributions of weekly EUR/JPY exchange rate predictions.

For the weekly NZD/CAD exchange rates, the *but* de-

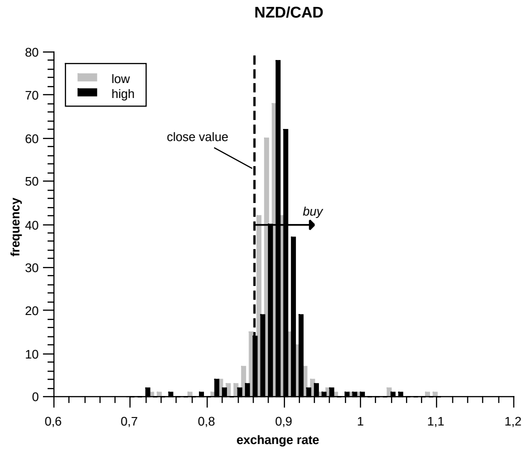

Figure 9: Composition of high-low distributions of weekly NZD/CAD exchange rate predictions.

cision gives a probability of profit $P_p = 0.89$ and a probability of loss $P_l = 0.11$ (Figure 9). In this scenario, the portfolio is constructed using equation 7 with only GBP/AUD and NZD/CAD data. The calculated weights are $W_{W,gbp/aud} = 0.42$ and $W_{W,nzd/cad} = 0.58$.

3.3 Comparison of Predictions

The accuracy of predictions based on our support system for investors is presented on Table 1. Each exchange rate prediction was evaluated according to the mean absolute percentage error (MAPE) when comparing the real future value with the mode of one of the predicted distributions: high in the case of a *buy* decision and low in the case of a *sell* decision. Our results demonstrate that daily predictions were more accurate than the weekly predictions.

Table 1: Comparison of the accuracy of daily and weekly predictions.

Exchange rate	MAPE (%) low	MAPE (%) high
GBP/AUD daily	0.198	0.319
EUR/JPY daily	2.250	1.051
NZD/CAD daily	0.412	2.164
GBP/AUD weekly	1.993	1.874
EUR/JPY weekly	3.696	4.737
NZD/CAD weekly	3.498	2.814

Our support system for currency market was tested on imitated market Oanda inreal time Results of trading using different strategies is presented in Figure 10. Strategy is determined by the choice of different risk levels of trading platform and choice of portfolios. Conservative strategy has 1:10 leverage and funds are shared equally. Moderate strategy has 1:20 leverage and the funds are divided in proportion to the projected profit. Aggressive strategy has 1:50 leverage and the funds are divided in proportion to the projected profit.

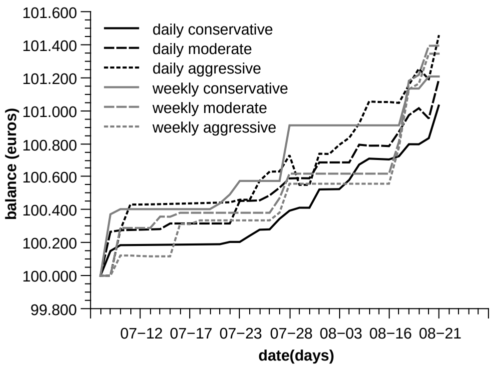

Figure 10: Comparison of daily and weekly balances of different trading strategies in period from 08-07-2015 to 21-08-2015.

Comparison of daily and weekly trading using different strategies shows sustainable growth of investment profit of all tests and allows to expect the good annual results (10-18 %). Our support system for currency market speculators uses modern portfolio theory for the diversification of risk. Orthogonality in an investment portfolio (equations (1) and (2)) reduces the risk of losing. A comparison of daily and weekly portfolios is presented in Table 2.

Total profit of daily and weekly portfolios are very similar, but weekly profit per trade is roughly twice more daily profits per trade. So investor can get same result with less trading time. Prediction of chaotic processes like financial markets, is not simple process where daily historical data easy can be changed by weekly data. Number of different events in one week can more easy change the tendencies then in one day. Lots of financial prediction tools can easy predict the tendencies, but cannot predict extremes of the price dynamic. Good tool of finance market prediction can recognize the coming changes.

Table 2: Comparison of daily and weekly portfolios.

portfolio	total profit	profit per trade
daily conservative	1030.44	38.2
daily moderate	1186.53	45.6
daily aggressive	1451.83	63.1
weekly conservative	1207.05	100.6
weekly moderate	1393.96	116.2
weekly aggressive	1345.23	112.2

Investment support system using the EVOLINO RNN ensemble is multilevel tool for investor. It concludes not only ensemble of EVOLINO RNN with function of prediction, but there are multilevel computation creativity too.

4 CONCLUSIONS

We have developed a support system for currency market investors by combining monitoring synergies between different branches of science (economics, mathematics, psychology, biology), the latest technological breakthroughs (online payments and artificial intelligence), and investor experience. The decision making support system is a useful tool for speculators in the relatively risky currency market. Our research aims to enhance future prospects. The comparison of daily and weekly predictions provides the ability to use the support system for the weekly forecasting of exchange rates. The accuracy of weekly forecasts is lower than that of daily predictions, but still accurate enough to enable successful trading. Weekly profit per trade is roughly twice more daily profits per trade. The support system requires multi-core hardware resources for timely data processing using MPI library-based parallel computation. Information obtained from the support system provides investors with an advantage in making investment decisions compared with uninformed market players.

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