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EVALUATION OF THE PORTFOLIO PERFORMANCE INDICATORS, USING EVOLINO RNN TRADING MODEL

Nijole Maknickiene

Vilnius Gediminas Technical University, Faculty of Business Management,
Saulėtekio ave. 11, LT-10223 Vilnius, Lithuania
Email: nijole.maknickiene@vgtu.lt

Abstract. The conditions for investment depend on correct forecasts of financial markets parameters received by artificial intelligence based on currency trading models, where AI was used as probabilistic forecasting tool. Improvements of predictions probability directly influence the investment portfolio performance indicators and their inter-relationship. Newly developed Evolino Recurrent Neural Network (RNN) based on forecasting model was used for study of influence of currency exchange rate forecasts on investment decisions related with reception and choice of investment strategy. Results of portfolio performance indicators and portfolio riskiness are presented.

Keywords: artificial intelligence, forecasting, investment portfolio, exchange rates, Sharpe ratio, skewness, Sortino ratio.

Jel classifiacation: G11, G15, G17.

1. Introduction

World well-known portfolio performance indices may help to assess the prediction system, disclose the investment opportunities and risks. Portfolio performance indicators were created for making the right investment decisions by assessment of historical data. In our case, the decision is made by system which uses artificial intelligence ability to predict.

Our trading model is based on Evolino RNN. EVOLINO stands for EVolution of recurrent systems with Optimal LINear Output. EVOLINO- based LSTM (Long Short Term Memory) recurrent networks learn to solve several previously unlearnable tasks. A new class of learning algorithms for supervised recurrent neural networks (RNN) was proposed by Schmidhuber *et al.* (2005) and developed in some Evolino publications: (Wierstra *et al*. 2005; Schmidhuber *et al*. 2007).

Fuzzy-Delphi system creators (Kuo *et al*. 1996; Chang; Wang, 2006) inspired us to an unstable one Evolino RNN prediction, change expert eight Evolino RNN system. The model using the Delphi method, and estimates the compatibility of the calculation to get a good prediction results.

Decision making strategy, proposed by Rutkauskas (2006), investment strategy choices, with the help of indicators describing investment efficiency- profitability, reliability and risk descripted in paper of Stasytyte, Rutkauskas (2008) was very helpful for making three different investment strategies for our model. The article made by Stasytyte, Rutkauskas (2011) was revealed a consistent way towards investment possibilities set description, when investment assets possibilities are under uncertainty. Comprehensive measurement system for assessing the overall performance and sustainability of companies was proposed by Stankeviciene (2011).

It is important to estimate statistical reliability, riskiness and profitability of each investment models and strategies. Sharpe (1994) proposed ratio measuring profitability per unit of risk. Price, Sortino (1994) replace standard deviation by downside deviation. Distributions of investment return or Sharpe index, its asymmetry can more accurately assess investment opportunities.

Dowd (2000) proposes a new rule for risk adjustment and performance evaluation. This rule is a generalization of the well-known Sharpe ratio criterion, and under normal conditions enables a manager to correctly assess alternative risky investments. Goetzmann *et al*. (2002) formulated optimal strategy rules for increasing the Sharpe ratio. The distribution of high Sharpe ratio managers should be compared with that of the optimal Sharpe ratio strategy.

Skewness is a measure of the asymmetry of probability distributions. Modern finance is heavily based on the unrealistic assumption of normal distribution. This discussion aims to highlight the importance of skewness in asset pricing. The skew is important for analysis based on normal distributions incorrectly estimates expected returns and risk. Asset returns distribution have systematic skewness, expected returns should include rewards for accepting this risk. Conditional skewness helps explain the cross sectional variation of expected returns. (Siddique, Harvey 2000).

Sharpe ratio has been studied and criticized by Christie (2005). Estimators of the Sharpe ratio have less helpful distributions than estimators of mean and variance. The error in the estimate of the Sharpe ratio can be simply too large to make useful conclusions and to make right decision to invest.

The Adjusted for Skewness Sharpe Ratio (ASSR) is most natural extension of the Sharpe ratio. This measure takes into account introduction the skewness of return distribution. Zakamouline and Koekebakker (2008) show that maximizing the ASSR is consistent with maximizing expected utility, it is most natural extension of the Sharpe ratio. This measure takes into account the skewness of return distribution and we denote it as the Adjusted for Skewness Sharpe Ratio (ASSR). Zakamouline and Koekebakker (2009) was presented the study of the investor’s preferences to higher moments of distribution. Eling and Tibiletti (2010) redesign the classical Sharpe ratio for skew normal distributions. This new skew-normal Shape ratio consistently moves with skewness and no distorted information on performance is provided. An empirical investigation illustrates skew normality of mutual and hedge fund returns.

The aim of the paper is to investigate exchanges of investment portfolio performance indicators, when AI system are predicting exchange rates. This research includes profitability, riskiness, profitability per unit of risk (Sharpe ratio), Adjusted for skewness Sharpe ratio (ASSR), profitability per unit losses (Sortino ratio). Three different strategy of investment illustrates the large choice of investor, using Evolino RNN trading system.

2. Prediction model and portfolio performance indicators

2.1. Model based in Evolino RNN

Our earlier article (Maknickiene, Maknckas 2012) introduced the AI tool - it is Evolino RNN-based forecasting and investment decision-making model. Evolino was developed by (Schmidhuber *et al*. 2005; Wierstra *et al.* 2005; Schmidhuber *et al*. 2007).

Getting historical financial markets data from FOREX market, we choose for prediction EUR/USD (Euro and American Dollar), EUR/JPY (Euro and Japanese Yen), USD/JPY (American Dollar and Japanese Yen), EUR/CHF (Euro and Swiss Franc) exchange rates and their historical data for the first input, and for the second input, two years historical data for XAUUSD (gold price on American Dollar), XAGUSD (silver price on American Dollar), QM (Oil price in American Dollar), and QG (gas price on American Dollar). At the end of this step we have a basis of historical data.

The python script calculates the ranges of orthogonality of the last 80–140 points of the exchange rate historical data chosen for prediction, and an adequate interval from the two years historical data of XAUUSD, XAGUSD, QM, and QG (Maknickas, Maknickiene 2012). A value closer to zero indicates higher orthogonality of the input base pairs. Eight pairs of data intervals with the best orthogonality were used for the inputs to the Evolino recurrent neural network.

Eight Evolino recurrent neural networks made predictions for a selected point in the future. All Evolino RNN parameters are selected for optimal learning and prediction. (Rutkauskas *et al*. 2011). At the end of this step, we have eight different predictions for one point of time in the future.

The resulting eight predictions are arranged in ascending order, and then the median, quartiles, and compatibility are calculated. If the compatibility is within the range [0; 0.024], the prediction is right. If not, then step 3 is repeated, sometimes with another ‘teacher’ if the orthogonality is similar. At the end of this step, we have one most probable prediction for the chosen exchange rate.

Repeating steps 1–4 for the other exchange rates lets us have a set of exchange rate forecasts and to build an investment portfolio. The first portfolio is made from the four exchange rates (EUR/USD, EUR/JPY, USD/JPY, EUR/CHF), and the investment amount is divided equally at every step of the investing. The second portfolio is made from the four same exchange rates but the amount invested is divided by the projected percentage gain. The third choice of investment portfolio consists of that exchange rate whose projected growth rate is the highest. The basic architecture of the prediction algorithm is shown in Figure 1.

In previous works (Maknickiene, Maknickas 2012) it was found that the average probability of the model to predict changes in market direction is - 0.77.

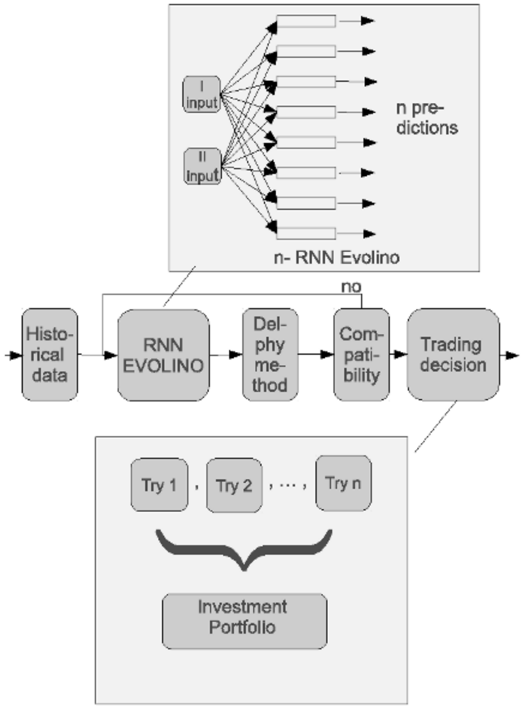

Fig. 1. Scheme of the model (Source:compiled by autor)

2.2. Investment portfolios

Having several different exchange rate forecasts allows the investor to choose different investment portfolios and to reduce the investment risk, thus increasing its reliability. Three investment portfolios have been tested:

Conservative. The first portfolio was made from the four exchange rates (EUR/USD, EUR/JPY, USD/JPY, EUR/CHF) with the investment amount divided equally at every step of investing (3 days in our research). The investor, having four predictions from the model, chooses one from the three operations *buy* – if the exchange rate will increase, *sell* – if the exchange rate will decrease, and *keep* – if the prediction has some doubt, such as very high variation. Every operation with exchange rates has a damage equal to 0.02 from the operation.

Moderate. The second portfolio is made from the four same exchange rates. The investor, having four predictions from the model, in order to maximize profits, divides the initial investment amount by the projected percentage gain.

Aggressive. The third portfolio is made from the same exchange rates but the entire amount is invested in only one exchange rate, that with the biggest predicted profit.

Model, investment management system and its reliability are further described in paper (Maknickiene, Maknickas 2012).

2.3. Portfolio performance measures

We investigated those of portfolios performance measures:

- profitability, experimental distribution of returns in every three trading days by our model;
- riskiness, moving averages of standard deviation σ;
- profitability per unit of risk (Sharpe ratio). The standard Sharpe ratio SR could be calculated by:

$$SR = \frac{\mu - r}{\sigma}\sqrt{\Delta t} \tag{1}$$

were μ is a mean and r is the risk-free interest rate per unit of time.

- Adjusted for skewness Sharpe ratio (ASSR);
- profitability per unit losses (Sortino ratio).

Theorem (Zakamouline, Koekebakker 2009): *If in the infinite Taylor series we keep the terms up to* $\Delta t^{2/3}$ *and disregard the terms with higher powers of* Δt*, then the solution for optimal a is given by*

$$a \approx \frac{SR}{\gamma\sigma\sqrt{\Delta t}}(1 + b_3 \frac{Skew}{2} SR) \tag{2}$$

where γ is the Arrow–Pratt measure of absolute risk aversion:

$$\gamma = \frac{U^{(2)}(\omega_r)}{U^{(1)}(\omega_r)} \tag{3}$$

where $U^{(n)}$ denotes the nth derivative of utility function. The investor has a wealth of ω and invests a in the risky asset and, consequently, ω − a in the risk-free asset.

So the following expression for the investor's maximum expected utility is:

$$E\,|U(\omega)| \approx U(\omega_1) + \frac{U^{(1)}(\omega_1)}{\gamma}\frac{1}{2}SR^2(1 + b_3\frac{Skew}{3}SR) \tag{4}$$

where *Skew* is the skewness of the distribution of *x* defined by

$$Skew = \frac{E[\left(x - E\left([x]\right)\right)^3]}{E[\left(x - E\left([x]\right)\right)^2} \tag{5}$$

and b_3 is the investor's relative preference to the skewness of distribution. The proof is given in Zakamouline,Koekebakker (2009) article.

The mean-variance approximation of the expected utility can be justified by assuming that Δt is very small. If we increase Δt and make it "rather" small, to improve the approximation we need to take into account the skewness of distribution. Generally, the longer Δt the more terms we need in order to provide a good approximation of the expcted utility by means of a Taylor series.

In the mean-variance-skewness framework of Theorem the investor's individual performance measure can be given by

$$ASSR = SR\sqrt{1 + b_3 \frac{Skew}{3} SR} \tag{6}$$

where ASSR stands for Adjusted for Skewness Sharpe Ratio, under condition that ASSR is a positive real number.

3. Evolution of portfolio performance indicators

Each investment will inevitably associated with the risk of losing investments. By comparing markets standard deviations and the three investment strategies - conservative, moderate and aggressive – the three tests of the average standard deviations of moving averages distributions shown in Figure 2. Most risky investment portfolio is aggressive and it is as markets own riskiness, less risky is moderate and least risky conservative investment portfolio.

Standard deviation measures the volatility of investment proposals result, risk level. When the standard deviation is higher, the wider the range can vary the expected score, the riskier the investment proposal, and vice versa. The standard deviation shows the expected net present value of the investment in the dissemination of 0.38 in conservative strategy, moderate - 0.53, aggressive in range 0.81.

Profitability dependences on risk presented in Figure 3. The result is reflected in clusters of each investment strategy options for different investment strategies.

The Sharpe index moving averages for each investment strategy and exchange market own moving Sharpe index averages was calculated by (1) formulas. Comparing the investment strategies Sharpe index moving averages distributions with the same period of exchange rate moving averages Sharpe index distributions (Fig. 4), we observe that distributions investments by our model, have a greater right skew 2.08 and average 0.74 for conservative investment strategy, skew 2.26 and average 0.79 for moderate, skew 2.51 and average 0.84 for aggressive and its are more then skew 0.79 and average 0.42 for the four selected currency exchange rates own Sharpe index distributions skew and average. For the investors, it means that the investment support system is more useful than the selected safe investment with a 3% profit per annum. Positive foreign exchange market Sharpe ratio can be determined as economic growth or other exchange market operating on external conditions.

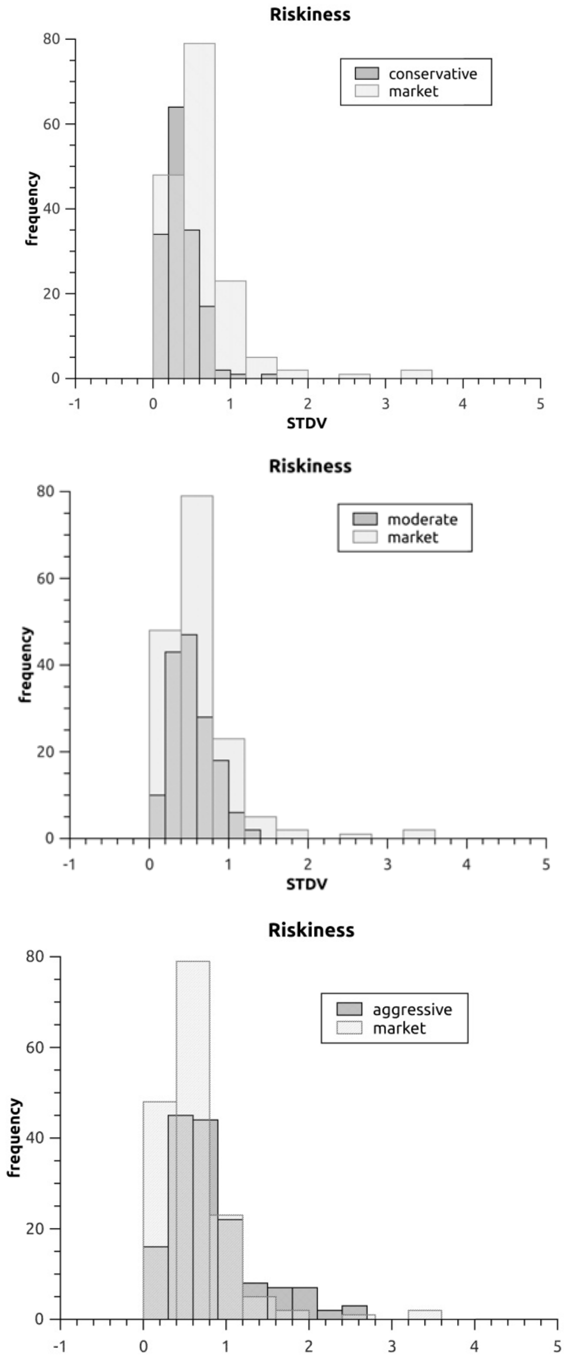

Fig. 2. Distributions of moving averages of standart deviations in three investment strategies

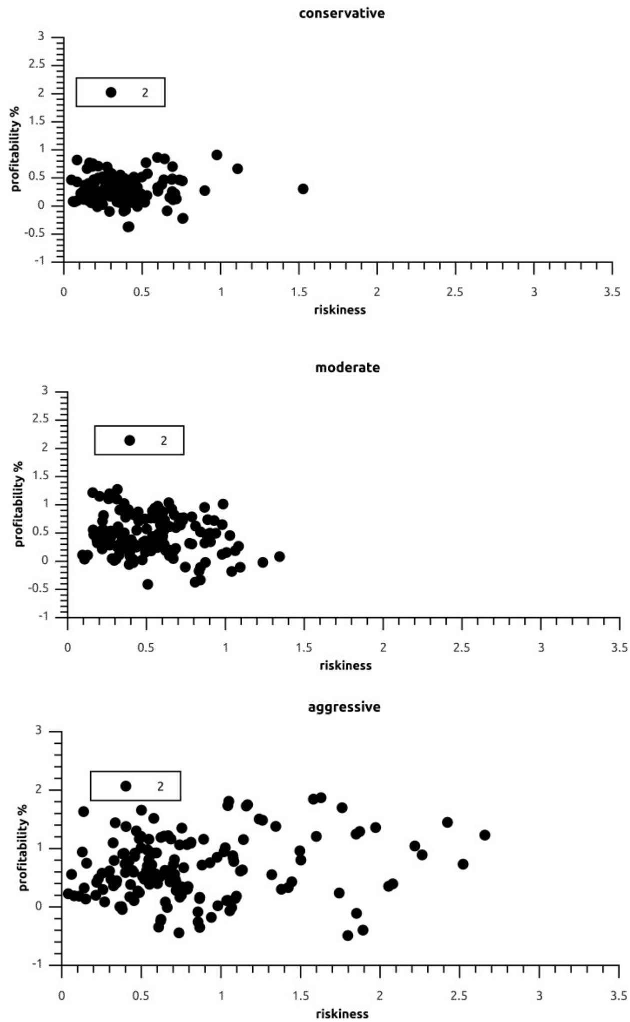

Fig. 3. Profitability dependences of risk for three different investment strategies

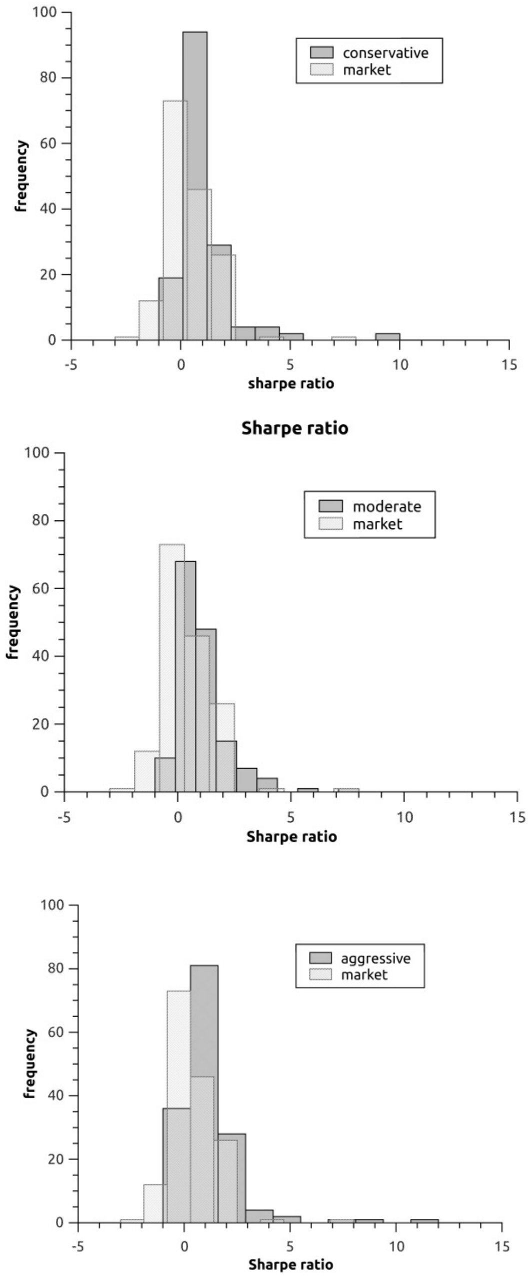

Fig. 4. Sharpe ratio for three different investment strategies

Adjusting for Skewness of Sharpe Ratio (ASSR) assess the portfolio return on a quite asymmetry. Right Skewness refers to the expected increase in profitability. (Gatfaoui 2010).

Sortino ratio reflects investors' expectations - it only takes into consideration the negative standard deviations. Conservative portfolio Sortino index average is 1.13, moderate portfolio 1.28 and aggressive portfolio 1.22. All Sortino indexes are very high, it suggests that the support system for investors with low risk of loss.

Portfolio performance parameters for three investment strategies and four exchange rates own indexes are in table 1.

Table 1. Portfolio performance parameters for three investment strategies (Source: compiled by author)

Portfolio strategy	Profitability %	Riskiness σ	Sharpe ratio average	Sharpe ratio Skew	ASSR average	Sortino ratio average
conservative	0.31	0.38	0.74	2.08	0.92	1.13
moderate	0.45	0.53	0.79	2.26	1.01	1.28
aggressive	0.70	0.81	0.84	2.51	1.07	1.22
market	0.31	0.72	0.41	0.79	0.45	0.55

Results in table 1 shows that the market's own profitability meets a conservative investment strategy, but it is much smaller, than the profitability of moderate and aggressive strategies. Market own risk exposure corresponds aggressive strategy but it is more than conservative and moderate strategies risk. The markets Sharpe ratio is below the model predicted the strategy Sharpe indicator averages. Market corresponding measures are much lower than the parameters, predicted by model, like skewness of distributions, ASSR ratio and Sortino ratio.

4. Conclusions

Portfolio performance indicators evaluate the model's ability to predict the past, but can not predict the future. They can provide information about the reliability of the model, risk profile and expected profitability, which may be useful for prediction model development and debugging phase.

Portfolio performance indicators can provide investors with more information, selecting an investment strategy, creating investment portfolios.

Moving averages of profitability and Sharpe ratio distributions skewness and ASSR index best reflects the actual prediction of this model results. Graphically visible distributions shift to the positive side reflects the possibilities of the investment strategy.

Maximizing the skew to right of distributions of profitability and Sharpe ratio, ASSR are consistent with maximizing expected utility.

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Nijole MAKNICKIENE, master on Physics at Vilnius University 1986. Recently assistant at the department of Finance Engineering of Vilnius Gediminas Technical University.. Research interests: Capital markets, Researching chaotic processes by neural networks.