

# Two-Period-Ahead Forecasting For Investment Management In The Foreign Exchange

Konstantins KOZLOVSKIS, Natalja LACE, Julija BISTROVA, Jelena TITKO  
Faculty of Engineering Economics and Management, Riga Technical University  
1/7 Meza Str., Riga, LV-1007, Latvia

## ABSTRACT

Modern trading platforms with built-in programming languages and application of programming interfaces allow implementation of econometric methods in financial instruments trading. Offline testing of the developed strategies gives an opportunity to estimate the efficiency of investment management based on such trading technology.

Autoregressive models ensure sufficient approximation of the financial time series. The main idea of the paper is to check the possibility of using two-period-ahead forecasting in trading on foreign exchange taking into account some limitations described in the paper. Using this feature of autoregressive models the efficiency of two-period-ahead forecasting is evaluated in this paper as a part of the simplest trading strategy on foreign exchange. The trading strategy is based on opening the position on daily average prices predicted by one-period-ahead forecasting and closing the position on take profit level predicted by two-period-ahead forecasting.

The advantages and disadvantages of two-period-ahead forecasting implementation in investment management are discovered when testing the trading strategy on foreign exchange. After estimation of the trading statistics some optimizations are made in the initial trading strategy.

**Keywords:** two-period-ahead forecasting, investment management, foreign exchange

## 1. INTRODUCTION

The dynamics of the price movements of financial instruments on the financial markets creates the necessary prerequisites for speculative trading. High liquidity and volatility favors the development of trading strategies which can take into account the features of price fluctuations. The development of trading platforms and built-in programming languages allow any investor to implement any mathematical apparatus in an automated trading system.

Nowadays there are lots of scientific researches and methods devoted to investment management on the financial markets of different types and development.

One of the most popular directions of financial markets analysis is related to univariate and multivariate copulas which are based on the Sklar's theorem ([2]) and described by different researchers ([9]). The theory of copula allows to study nonlinear dependences between selected assets and to build unified distribution function based on the distribution functions of each asset. In the theory of copula the set of financial instruments can be considered as one asset. The use of the theory of copula in investment management shows effective results in raising capital ([14], [6]) but its implementation is very labor-intensive un complicated. The second broad class is based on ARCH-like models introduced by introduced by Engle in 1982 ([10]) and generalized by Bollerslev in 1986 ([12]). Developing ideas of ARCH-like models and the theory of copulas a new class of models has been created named copula-based ARCH-like models proposed by Patton in 2000 ([1]), Jondeau and Rockinger in 2001 (0) and extended to copula multivariate GARCH models by Lee and Long in 2005 ([13]). The third class of forecasting models in the field of financial markets is represented by artificial intelligence systems. The use of neural networks in predicting the dynamics of a financial instrument on a financial market is broadly introduced by many papers. For example, Piche used a trend visualization plot based on a moving average ([11]); Dempster, Payne, Romahi and Thompson considered some strategies which use a collection of popular technical indicators as input and seek a profitable trading rule defined in terms of them ([8]); Chan and Teong showed some improvements in trading based on technical analysis ([7]), and many other papers.

In this paper the authors attempt to implement simple investment strategy on foreign exchange with two-period-ahead forecasting based on simple autoregressive models. This strategy is very simple and implementable in used trading software without any complications.

## 2. METODOLOGY

In this research two-period-ahead forecasting is based on a number of key assumptions:

- Daily average prices as initial data. Forecasting average daily prices in the future increases the possibility of capturing average prices in case of high volatility on the market. On the other hand,

average daily prices are very suitable for autoregressive models.

- Simple autoregressive models as a base of two-period-ahead forecasting. As mentioned before, the quality of average daily prices approximation by autoregressive models is quite high in case of financial time series. Also, autoregressive models are very simple to be programmed and implemented in automated investment management systems without any complications.
- Liquid and volatile financial instruments. Liquidity and volatility of a financial instrument are very important in case of speculative short-term trading. Liquidity minimizes risk of non-execution of a pending order at the corresponding price. Volatility increases the possibility of reaching forecasted take-profit level because of wide range of price fluctuations. That is why foreign exchange is more preferable market because of its high volatility and high liquidity that exceeds 1 trillion USD of daily turnover in the spot-market ([3]).

In this research the authors used a simple autoregressive model AR(p) without intercept for two-period-ahead forecasting. A simple AR(p) model can be presented as follows:

$$y_t = \sum_{i=1}^p a_i y_{t-i} + \varepsilon_t \quad (1)$$

where  $p$  – the order of autoregression;  
 $a_i$  – the autoregression coefficients;  
 $y_t$  – the time series under investigation;  
 $\varepsilon_t$  – the noise term.

The main idea of this research is to test the efficiency of two-period-ahead forecasting by the simplest autoregressive models in automated trading in foreign exchange. If a simple autoregressive model can predict the average daily price of a currency pair quite well, an automated trading system can be built on this feature (see Figure 1).

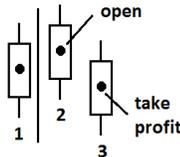


Figure 1 Two-period-ahead forecasting implementation in trading

At the end of the trading day (1) the next average daily price is calculated by the autoregressive model estimated earlier. Pending orders are set at this forecasted average daily price towards the forecasted average daily price for “the day after tomorrow” (3). Thus, two-period-ahead

forecasting can be expressed by the following simple formula

$$y_{t+2} = \sum_{i=1}^p a_i y_{t+2-i} + \varepsilon_{t+2} \quad (2)$$

Volatility is a very important factor in this particular case of two-period-ahead forecasting. Due to the wide range of price fluctuations, which means increased volatility, the probability of reaching take-profit level in “the day after tomorrow” (day 3 in the Figure 1) is increased as well.

### 3. EMPIRICAL RESULTS

The authors analyzed the most liquid currency pairs on the foreign exchange. According to the statistical information from the Bank for International Settlements, the most tradable currency pairs are EURUSD, USDJPY, GBPUSD, AUDUSD, USDCHF, USDCAD, EURJPY, EURGBP and EURCHF. The descriptive statistics of currency pairs indicates their sufficient volatility. The average daily prices were used for each currency pair from January 1, 2004 to May 1, 2012.

#### 3.1. Model estimation

The autoregressive models were estimated based on the average daily prices of 2004. The orders of the estimated autoregressive models are shown in the Table 1.

Table 1 The estimated AR(n) models on the average daily prices of 2004

No	Currency pair	Model	R-squared	DW stat	Sample size
1	EURUSD	AR(3)	0.9854	1.9305	262
2	USDJPY	AR(4)	0.9764	1.9908	263
3	GBPUSD	AR(4)	0.9705	1.9722	263
4	AUDUSD	AR(4)	0.9850	1.9671	261
5	USDCHF	AR(3)	0.9835	1.9317	262
6	USDCAD	AR(4)	0.9940	1.9608	261
7	EURJPY	AR(3)	0.9615	1.9458	263
8	EURGBP	AR(4)	0.9841	2.0104	263
9	EURCHF	AR(3)	0.9859	1.9465	262

Estimation of the parameters of the autoregressive models demonstrates that the R-squared statistic is very close to 1.0, indicating that the fraction of the variance of the dependent variable is explained by the independent variables very well. In fact, high R-squared statistics is very typical in autoregressive models analyzing financial time series.

The DW statistic in the output is around 2.0 indicating the potential absence of serial correlation in the residuals. The absence of serial correlation was confirmed by using critical values for the Durbin-Watson test at 5% significance level (see Table 2) (0).

Table 2 The critical values for the DW test at 5% significance level (no intercept)

No	Currency pair	k	For positive corr.	For negative corr.	Result
1	EURUSD	3	1.634	1.728	no serial corr.
2	USDJPY	4	1.718	1.624	no serial corr.
3	GBPUSD	4	1.718	1.624	no serial corr.
4	AUDUSD	4	1.718	1.624	no serial corr.
5	USDCHF	3	1.634	1.728	no serial corr.
6	USDCAD	4	1.718	1.624	no serial corr.
7	EURJPY	3	1.634	1.728	no serial corr.
8	EURGBP	4	1.718	1.624	no serial corr.
9	EURCHF	3	1.634	1.728	no serial corr.

Thus, statistically significant autoregressive models were estimated for each currency pair. For instance, the autoregressive model for the currency pair EURUSD can be written as

$$\text{EURUSD}_t = 1.4411 * \text{EURUSD}_{t-1} + (-0.7404 * \text{EURUSD}_{t-2}) + 0.2995 * \text{EURUSD}_{t-3} \quad (1)$$

### 3.2. Investment management based on two-period-ahead forecasting

Using the estimated autoregressive models for each currency pair on the average daily data of 2004, the trading system was programmed and implemented in MetaQuotes trading platform. Setting pending orders at one-period-ahead forecasted average daily prices with take-profit levels based on two-period-ahead forecasted average daily prices, the efficiency of two-period-ahead forecasting was evaluated without re-estimating the autoregressions parameters. It means that trading was made on the basis of the autoregressive model built on average daily data of 2004. Some realized trading statistics is shown in the Table 3.

Table 3 Trading results statistics

No	Currency pair	Results, pips <sup>1</sup>								
		2005	2006	2007	2008	2009	2010	2011	2012 <sup>2</sup>	Total
1	EURUSD	232	306	249	-982	295	-605	400	-227	-332
	<i>Aver. profit/loss</i>	45/98	40/71	42/67	44/155	45/142	47/131	44/170	39/103	
	<i>Win rate</i>	69.92%	66.10%	63.16%	74.45%	76.87%	70.97%	81.13%	72.73%	
2	USDJPY	-200	-450	125	-349	397	-136	378	52	-183
	<i>Aver. profit/loss</i>	47/56	35/55	41/96	35/152	40/75	53/61	54/55	57/34	
	<i>Win rate</i>	45.45%	39.13%	73.91%	72.73%	77.78%	47.62%	68.42%	44.44%	
3	GBPUSD	204	-844	-492	-297	1227	-134	608	937	1209
	<i>Aver. profit/loss</i>	45/116	43/94	44/109	52/172	48/171	46/112	43/125	43/71	
	<i>Win rate</i>	72.92%	64.06%	68.70%	75.85%	82.44%	70.21%	77.04%	85.71%	
4	AUDUSD	-223	726	-301	-715	1449	240	-283	484	1377
	<i>Aver. profit/loss</i>	42/55	40/44	40/66	45/105	42/104	40/92	40/108	45/47	
	<i>Win rate</i>	54.47%	60.71%	60.00%	66.42%	78.63%	71.31%	70.59%	78.95%	
5	USDCHF	-390	53	-1088	-357	-609	492	-2099	402	-3596
	<i>Aver. profit/loss</i>	38/88	31/60	30/59	39/108	36/123	39/83	47/129	38/46	
	<i>Win rate</i>	67.69%	66.40%	55.83%	71.63%	74.82%	70.63%	62.83%	73.08%	
6	USDCAD	-1618	-782	276	-1645	1521	-1885	-695	171	-4657
	<i>Aver. profit/loss</i>	34/71	39/71	46/99	40/284	45/97	38/97	41/68	38/51	
	<i>Win rate</i>	56.43%	55.56%	70.89%	78.57%	79.79%	60.00%	56.00%	62.50%	
7	EURJPY	-683	-187	112	-1247	372	-463	-1708	-	-3804
	<i>Aver. profit/loss</i>	54/186	49/133	59/180	64/273	75/182	48/118	51/232	-	
	<i>Win rate</i>	65.22%	69.23%	77.27%	67.86%	75.86%	55.56%	54.55%	-	
8	EURGBP	-598	10	-343	-2049	-3403	219	334	-	-5830
	<i>Aver. profit/loss</i>	45/49	35/38	37/44	62/125	58/140	62/98	61/88	-	
	<i>Win rate</i>	46.15%	52.08%	50.00%	57.63%	54.29%	62.39%	61.17%	-	
9	EURCHF	-229	-573	-900	380	1089	-415	-52	-132	-832
	<i>Aver. profit/loss</i>	28/35	33/35	37/59	50/100	37/58	38/71	49/120	15/14	
	<i>Win rate</i>	50.75%	41.67%	51.58%	68.75%	71.68%	62.07%	70.79%	38.10%	
Total										-16648

<sup>1</sup> The value of one pip depends on used lot size and quantity of signs after the comma in price. For instance, in 4-digits trading systems 1 pip  $\approx$  10 USD for 1.0 lot,  $\approx$  1 USD for 0.1 lot and  $\approx$  0.1 USD for 0.01 lot. One lot equals 100 000 USD.

<sup>2</sup> From January 1, 2012 to May 1, 2012 (including)

In the Table 3 the win rate values indicate that overall the two-period-ahead forecasting is effective from the predictability point of view. Take-profit levels predicted by the autoregressive models are successfully reached in more than 60% cases excluding several examples.

The analysis of average profit/loss ratio in the Table 3 shows that in most cases this ratio exceeds 1:2, i.e. at the

favorable win rate conditions profit growth generated by small take profits is neutralized by greater stop losses. As a result, an investor receives net losses.

Analyzing the trading results, the authors make a conclusion that the autoregressive models can predict the right price movements in “the day after tomorrow” but because of small predicted profits this trading technique is not efficient. It is obvious that this technique has to be optimized taking into account strong feature of two-period-ahead forecasting power.

### 3.3. Optimized investment management based on two-period-ahead forecasting

Taking into account the profit/loss ratios and win rate values, trading strategy can be further optimized by using stop loss and take profit levels. Win rate can be decreased if the profit/loss ratio will be at least 1:1 or better, i.e. 1.5:1 or 2:1.

In the optimization process all possible combinations were evaluated:

1. Take profit definition
  - by the autoregressive model
  - by fixed take profit level
  - without take profit level (closing opened trading positions at the end of a trading day).
2. Stop loss definition
  - by fixed stop loss level
  - without stop loss level (closing opened trading positions at the end of a trading day).

The authors proceeded with the optimization process by making an assumption that forecasted value by two-ahead-forecasting is defined when buying or selling a currency pair.

Optimization process was made on the period of 2004 to check how new investment management system based on the data of 2004 affects the results in next years.

The results of trading system optimization are shown in the Table 4.

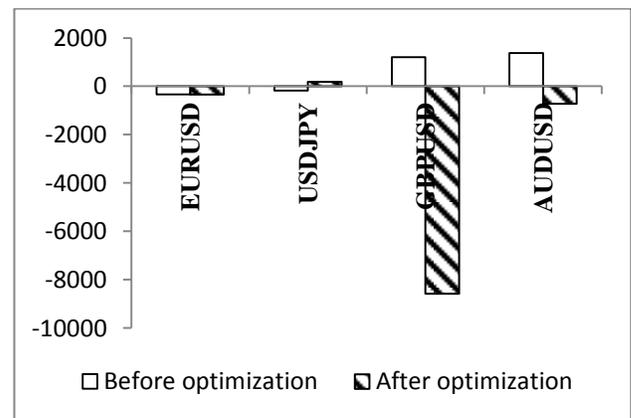
Table 4 The results of optimization process

No	Currency pair	Stop loss, pips	Take profit, pips	Model
1	EURUSD	70	-	No TP
2	USDJPY	30	-	No TP
3	GBPUSD	80	-	No TP
4	AUDUSD	20	-	No TP
5	USDCHF	90	-	No TP
6	USDCAD	20	-	No TP
7	EURJPY	50	-	No TP
8	EURGBP	90	20	Fixed TP
9	EURCHF	70	20	Fixed TP

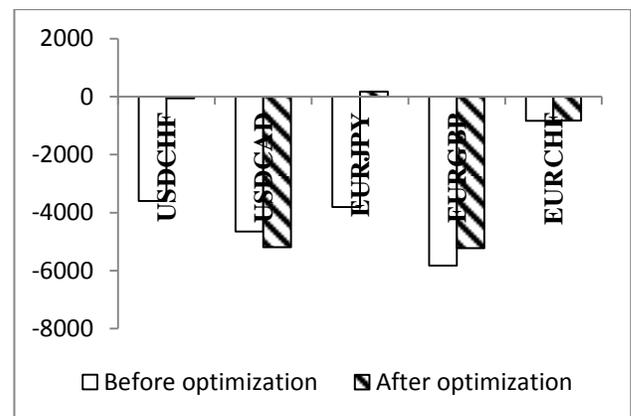
According to the optimized results, seven currency pairs should be traded without take-profit levels but with set stop-loss levels. Two currency pairs should be traded with take-profit and with stop-loss levels.

Some statistics of the realized trading with optimized investment management is shown in the Table 5. Comparison of the total results before and after optimization clearly shows that the results after optimization are worse. Before optimization the total loss on 9 currency pairs was 16648 pips (see the Table 4) but after optimization – 20565 pips (see the Table 5).

Comparison of the total trading results demonstrates that the optimization does not add value with the exception of the following currency pairs: USDJPY, USDCHF and EURJPY (see the Graph 1 and 2).

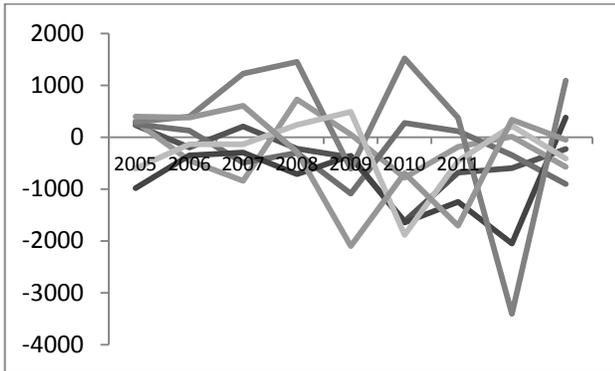


Graph 1 Comparison of the results before and after optimization on EURUSD, USDJPY, GBPUSD and AUDUSD, pips

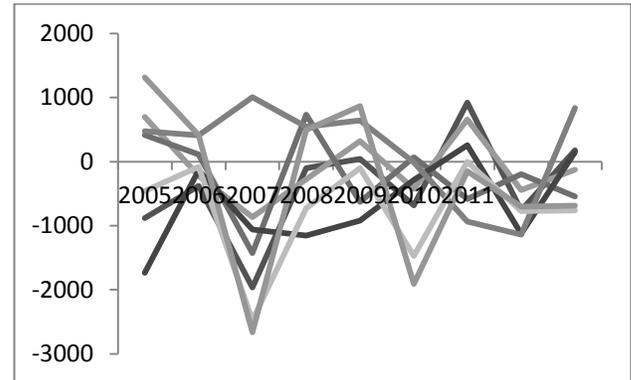


Graph 2 Comparison of the results before and after optimization on USDCHF, USDCAD, EURJPY, EURGBP and EURCHF, pips

When analyzing the dynamics of profits and losses between currency pairs it is seen that before optimization the profits and losses are less interrelated (see the Graph 3) showing scarcely noticeable downtrend in the total portfolio profit or loss.



Graph 3 The dynamics of profits and losses on 9 currency pairs over investigated time period before optimizations, pips



Graph 4 The dynamics of profits and losses on 9 currency pairs over investigated time period after optimizations, pips

After optimization the dynamics of profits and losses between currency pairs is more correlated (see the Graph 4) showing some convergence towards zero over the investigated time period. Total trading statistics after optimization is shown in the Table 5. The analysis of the results confirms the statement that historical results do not guarantee the same results in the future. In the Table 5 it is shown that the profitable investment strategy in 2004 is not so successful in the future time periods.

Despite the fact of increasing average profit/loss ratio and decreasing win rate basically for all currency pairs the total result on each financial instrument is negative with the exception of USDJPY and EURJPY which can be also ignored because of small and actually non-significant profit during seven and half years.

Table 5 Optimized trading results statistics

No	Currency pair	Results, pips								
		2005	2006	2007	2008	2009	2010	2011	2012 <sup>3</sup>	Total
1	EURUSD	-880	695	412	-1737	473	-459	1314	-152	-334
	<i>Aver. profit/loss</i>	71/62	59/57	65/55	130/67	126/67	111/63	123/66	69/70	
	<i>Win rate</i>	41.03%	54.72%	49.06%	26.98%	36.50%	34.17%	40.15%	46.67%	
2	USDJPY	-378	-223	112	-135	408	-84	412	76	188
	<i>Aver. profit/loss</i>	73/27	53/26	65/26	104/29	87/32	138/36	91/35	194/39	
	<i>Win rate</i>	12.00%	20.83%	33.33%	17.39%	37.50%	18.18%	47.06%	25.00%	
3	GBPUSD	-1961	-865	-1428	-1059	1005	-2472	-2663	869	-8574
	<i>Aver. profit/loss</i>	106/74	91/73	92/68	180/78	197/78	100/76	84/72	152/55	
	<i>Win rate</i>	32.82%	40.17%	35.29%	27.07%	31.16%	32.84%	32.23%	50.00%	
4	AUDUSD	-101	-277	731	-1156	544	-728	493	-230	-724
	<i>Aver. profit/loss</i>	59/20	57/20	88/20	144/20	119/20	100/20	135/20	70/20	
	<i>Win rate</i>	24.52%	23.36%	23.34%	8.24%	16.88%	12.67%	15.89%	10.53%	
5	USDCHF	43	321	-627	-921	645	-102	867	-283	-57
	<i>Aver. profit/loss</i>	72/58	60/55	44/53	104/70	87/71	65/68	116/82	75/74	
	<i>Win rate</i>	45.05%	50.47%	48.60%	35.65%	48.31%	50.43%	45.63%	41.67%	
6	USDCAD	-684	-423	67	-286	-13	-1473	-1910	-464	-5186
	<i>Aver. profit/loss</i>	104/16	83/18	102/18	259/19	168/18	64/19	59/20	52/19	
	<i>Win rate</i>	8.26%	13.64%	15.70%	5.88%	9.60%	13.22%	10.56%	15.38%	
7	EURJPY	922	656	-582	257	-934	0	-149	0	170
	<i>Aver. profit/loss</i>	153/58	120/60	98/63	242/63	144/62	-	123/63	-	
	<i>Win rate</i>	45.83%	46.43%	22.73%	24%	14.29%	-	30.77%	-	
8	EURGBP	-761	-446	-194	-1124	-1139	-774	-704	-80	-5222
	<i>Aver. profit/loss</i>	28/67	23/41	27/44	26/105	29/118	28/105	27/103	20/52	
	<i>Win rate</i>	62.11%	57.63%	59.48%	74.32%	75.33%	74.64%	74.80%	69.05%	
9	EURCHF	174	-129	-543	147	835	-761	-686	137	-826
	<i>Aver. profit/loss</i>	18/42	19/36	19/60	23/71	19/40	17/61	25/70	20/52	
	<i>Win rate</i>	72.22%	63.20%	71.01%	76.61%	78.08	71.11%	66.32%	85.71%	
Total										-20565

#### 4. CONCLUSIONS

This paper provides the development and implementation of two-period-ahead forecasting based on the simple autoregressive models on the foreign exchange. When testing efficiency of two-period-ahead forecasting in

<sup>3</sup> From January 1, 2012 to May 1, 2012 (including)

automated trading as one of the artificial investment management method the authors make the following conclusions:

1. In fact, the autoregressive models can predict average daily prices in “the day after tomorrow” and the win rate proves it. In most cases the win rate exceeds 60% of total trades. However, the ratio between small predicted profit and potential loss due to high volatility on the market neutralizes the positive effect of two-period-ahead forecasting based on the autoregressive models. That is why the high volatility of currency pairs on one hand allows to reach the forecasted price. However, on the other hand it has negative influence on the total profit because of inability to cover large losses with small profits even if the win rate is at investor’s favor.
2. Trading strategy optimization on historical data does not have any positive effect on the future result and potentially can worsen expected results.
3. To improve trading results on average daily prices another trading methodology has to be developed. It should be based on other principles of forecasting the dynamics of market fluctuations.

## 5. REFERENCES

- [1] A. J. Patton, (2000), Modelling Time-Varying Exchange Rate Dependence Using the Conditional Copula, Discussion Paper, University of California, San Diego.
- [2] A. Sklar, (1959). Fonctions de répartition à n dimensions et leurs marges. *Publ. Inst. Statist. Univ. Paris* 8, pp. 229-231.
- [3] Bank For International Settlements. Triennial Central Bank Survey, Report on global foreign exchange market activity in 2010. Monetary and Economic Department. <http://www.bis.org/publ/rpfx10t.pdf>
- [4] Durbin-Watson Significance Tables  
[http://www.eco.uc3m.es/~ricmora/MEI/materials/Durbin\\_Watson\\_tables.pdf](http://www.eco.uc3m.es/~ricmora/MEI/materials/Durbin_Watson_tables.pdf)
- [5] Jondeau, E. and Rockinger, M. (2001), The Copula-GARCH Model of conditional dependencies: an international stock-market application, *Journal of International Money and Finance*.
- [6] K. Kozlovskis, N. Lace, (2006) Challenges of Decision Making in the Latvian Equity Market // The 10th World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI 2006), pp. 137-143.

- [7] K.C.C. Chan, F.K. Teong, (1995). “Enhancing Technical Analysis in the FOREX Market Using Neural Networks.” *Proceedings of IEEE Conference on Neural Networks, Perth, Australia, Vol. 2*, pp 1023-1027.
- [8] M. A. H. Dempster, T.W. Payne, Y. Romahi, G.W.P. Thompson, (2001). “Computational Learning Techniques for Intraday FX Trading Using Popular Technical Indicators.” *IEEE Transactions on Neural Networks, Vol. 12 No.4*, pp 744-754.
- [9] R. B. Nelsen, (1999), *An Introduction to Copulas*, Springer-Verlag, New York.
- [10] R. F. Engle, (1982) Autoregressive conditional heteroscedasticity with estimates of variance of UK inflation, *Econometrica*, 50, 987-1008.
- [11] S. W. Piche, (1995). Trend Visualization. *Proceedings of IEEE/IAFE Conference on Computational Intelligence for Financial Engineering, New York City*, pp 146-150.
- [12] T. Bollerslev, (1986) Generalised autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31, 307-327.
- [13] T. H. Lee, X.D. Long, (2006), Copula-based Multivariate GARCH Model with Uncorrelated Dependent Errors, Working Paper.
- [14] V. Jansons, K. Kozlovskis, N. Lace, (2006). Portfolio Modeling Using the Theory of Copula in Latvian and American Equity Market. *Simulation In Wider Europe, 19th European Conference on Modelling and Simulation ECMS 2005*, pp. 628 – 632.

## 6. ACKNOWLEDGEMENTS

This paper has been prepared with support of the ERDF Project „The development of international cooperation, projects and capacities in science and technology at Riga Technical University”, Contract Nr. 2DP ./2.1.1.2.0/10/APIA/VIAA/003