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DIFFERENT PERIOD TIME SERIES FORECASTS INTEGRATION AS A TOOL OF INCREASING THE ACCURACY OF STOCK RETURN PREDICTION

Grigorij Žilinskij

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

Abstract. One of the key factors in ensuring the efficiency of investment is ability to obtain high-accuracy stock return forecasts. Nowadays, there are many different prediction methods, ranging from simple moving averages to neural networks and other sophisticated methods. The analysis of forecasting methods and proposals to integrate separate forecasts to improve prediction precision was carried out in this article. The method of separate forecasts integration, based on forecasting accuracy in past periods, was proposed. The empirical study validating the suitability of proposed method in integration of forecasts obtained analysing single and weighted moving averages (SMA and WMA) of different period time series was carried out.

Keywords: forecasting, time series, forecasts integration, prediction accuracy.

Jel classification: G17

1. Introduction

In my earlier article with Prof. A. V. Rutkauskas "Financial leverage usage for active management of the investment portfolio" we have proved that active portfolio management using financial leverage can be effective in order to increase the return on investment. However, due to relatively high transaction costs, it is crucial to have accurate stock return forecasts.

Time series analysis is one of the main methods in predicting stock prices and the expected profitability. Investor seeking to actively manage the investment portfolio is relevant to have accurate forecasts in the short term (e. g. one trading day). It is obvious that in order to forecast the expected return, investors will give priority to the most recent data analysis – will examine the daytime stock price changes in recent periods and less pay attention to the longer term (e. g. annual) stock price changes. However, financial crisis and the financial markets recovery after it have shown that the higher is the short or medium term downfall, the bigger stock price growth is usually following it and analysis of short term data without evaluation of the general trends can mislead investors. So it is necessary to integrate forecasts made analysing different period (cycle) time series.

The object of the research is the integration of different period time series forecasts.

The goal of the research is to create a method of integration different period time series forecasts, which enable to get more accurate stock return predictions.

Aiming to achieve the mentioned goal in the article is used: analysis and summarising of scientific information sources, graphical representation and comparison, quantitative mathematical and statistical methods.

2. Theoretical background

Markowitz (1952) introduced modern portfolio theory, which deals with portfolio selection problem. However he has not clearly defined, how must be evaluated expected stock return, only suggested, that "Perhaps there are ways, by combining statistical techniques and the judgment of experts, to form reasonable probability beliefs" (Markowitz 1952). In empirical research he uses arithmetical mean to evaluate expected return (Markowitz 1959). This approach was widely used by other scientists (Tvaronavičienė, Michailova 2004; Vasiliauskaitė 2004; Bikas, Laurinavičius 2009; Baixauli-Soler 2011). However some scientists (e. g. Bernstein and Wilkinson 1997) argue that geometric mean is more representative. Missiakoulis, Vasiliou and Eriotis (2010) not only evaluate possibilities to use arithmetic and geometric mean, but also propose to integrate them. Gilli and Kellezi (2000) propose to use scenario method for expected return evaluation.

The separate group of expected return evaluating methods are moving averages. Edwards and Magee (1992) identify four groups of moving average methods: single moving average (SMA), weighted moving average (WMA), exponential moving average (EMA) and linear moving average (LMA). Dzikevičius and Šaranda (2010) use EMA and SMA methods to forecast stock markets. The autoregressive moving average (ARMA) method and its modifications (MARMA, ARIMA, SARIMA) are also used for stock return prediction (Sallehuddin *et al.* 2007; Stevenson 2007; Jarret and Schilling 2008).

Stock price (return) forecasts can also be made using more sophisticated methods such as artificial neural networks (ANN), Hidden Markov model (HMM), genetic algorithms and others. Stock price prediction using ANN is analysed by Stern (1996), Kumar (2010), Leigh *et al.* (2002), Panda and Narasimhan (2010), Jandaghi (2010). Stock market forecasting using HMM is introduced by Hassan and Nath (2005). Araujo (2010) uses a quantum-inspired evolutionary hybrid intelligent (QIEHI) approach for stock price prediction. Li and Tsang (1999) suggested that genetic programming can improve technical analysis predictions.

There were also several attempts to integrate different forecasting methods. Chou *et al.* (1997) proposed a stock selection decision support system combining artificial intelligence and technical analysis. Nenortaite and Simutis (2006) proposed different ANN integration using Particle Swarm Optimization (PSO) algorithm to select the best ANN for the future investment decisions and to adapt the weights of other networks towards the weights of the best network. Lu *et al.* (2011) suggested integrated nonlinear independent component analysis (NLICA), support vector regression (SVR) and particle swarm optimization (PSO) stock index prediction model. Mehdi and Mehdi (2011) and Sallehuddin *et al.* (2007) proposed to combine non-linear and linear programming in integrated ANN-ARIMA model. Erlwein *et al.* (2011) were modelling financial time series using HMM and the Geometric Brownian motion (GBM) methods. Hassan *et al.* (2007) proposed an integrated HMM-ANN-GA model for stock price prediction. Afolabi and Olude (2007) have added an additional level of neurons to a standard neuron network, in which the best neurons for further analysis are selected. This model was called Hybrid Cohonen Self Organising Map (HCSOM).

Summarising the theoretical analysis of forecasting methods and proposals to integrate separate forecasts we can see that nowadays are a lot of forecasting methods, many scientists suggests methods integration to improve prediction accuracy. However, scientists suggest integrating entire forecasting methods, not the forecasts which were obtained using different methods. Integrating forecasts can be perceived in the Hybrid Cohonen Self Organising Map, if separate forecasts would be neurons in additional level. However, using HCSOM and selecting only best forecasts for further analysis cannot be effective, because not only best forecasts can be useful in improving prediction accuracy.

3. Forecasts integration method

To develop forecasts integration method I will start with different period time series forecasts integration. The graphical view of different period time series forecasts integration is shown at figure 1.

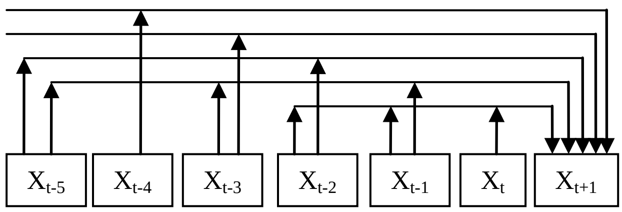

Fig.1. Different period time series forecasts integration

X_t in Fig. 1 is a stock return in period t, where t is the latest period, which data we have. X_{t+1} – return forecast for the nearest future period.

The analytical expression of different period time series forecasts integration method consists of two elements:

1. different period time series forecasts:

$$\begin{aligned}
X_{t+1}^1 &= f(X_t; X_{t-1}; X_{t-2}; ...; X_{t-n}) \\
X_{t+1}^2 &= f(X_{t-1}; X_{t-3}; X_{t-5}; ...; X_{t-2n-1}) \\
X_{t+1}^3 &= f(X_{t-2}; X_{t-5}; X_{t-8}; ...; X_{t-3n-2}) \\
&... \\
X_{t+1}^k &= f(X_{t-k+1}; X_{t-2k+1}; X_{t-3k+1}; ...; X_{t-kn-k+1})
\end{aligned} \quad ,(1)$$

2. forecasts integration into a consolidated estimate:

$$X_{t+1} = f(X_{t+1}^1; X_{t+1}^2; X_{t+1}^3; ...; X_{t+1}^k), \quad (2)$$

The method, consisting from two elements, needs different solutions for each element. To evaluate different period time series forecasts we can use single or even integrated methods analysed in the theoretical part of this article. Which method to use, investors can choose themselves.

For proper functioning of proposed different period time series forecasts integration method is essential to ensure efficient solutions in the second stage – forecasts integration into a consolidated estimate. The basic formula for forecasts integration is:

$$X_{t+1} = \sum \left(X_{t+1}^{k} \times w\left(X_{t+1}^{k} \right) \right), \qquad (3)$$

where:

X_{t+1} – integrated forecast;

X_{t+1}^{k} – k period length forecast;

$w\left(X_{t+1}^{k} \right)$ – weight of k period length forecast.

To propose an appropriate method for the integration of the individual forecasts we need to identify an appropriate benchmark (comparative basis), which will be used to calculate the weights of separate forecasts when integrating them into a one forecast. The main criteria evaluating prediction methods efficiency is an accuracy of forecasts made with it, so it is logical, that the integration principle will be based on prediction accuracy.

Summazing Firth and Gift (1999), Sallehudin (2007), Ho and Lee (1995), Antoniadis *et al.* (2006), Thawornwong and Enke (2004), Kumar (2009), Dutta *et al.* (2006), Yao *et al.* (1999) and Araujo (2010) there are these forecasts accuracy evaluation methods: forecast error (FE), absolute forecast error (AFE), mean square error (MSE), mean absolute forecast error (MAFE), root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute deviation (MAD), theil inequality coefficient (TIC), relative mean absolute error (RMAE), normalized mean squared error (NMSE), prediction of change in direction (POCID), and average relative variance (ARV).

Developing forecasts integration method it is not crucial to select the best forecast accuracy evaluation method. It could be a topic for further researches. So in this article I will use mean square error (MSE).

The formula for forecasts integration is:

$$X_{t+1} = \sum_{k=1}^{m} \frac{X_{t+1}^{k} \times \sum_{k=1}^{m} (MSE_{t}^{k})^{n}}{(MSE_{t}^{k})^{n} \times \sum_{k=1}^{m} \frac{\sum_{k=1}^{m} (MSE_{t}^{k})^{n}}{(MSE_{t}^{k})^{n}}} \quad ,(4)$$

where:

MSE_{t}^{k} – is k period length forecast's mean square error,

n – degree, used to enlarge the weight of the most accurate forecast in the integrated forecast (the best "n" will be proposed after empirical study results evaluation).

As we can see from formula 4, the biggest weight in integrated forecast will have non-integrated forecasts, which had the smallest mean square error in past period.

4. An empirical study

In the methodological part of the article was introduced different period length time series forecasts integration method. Its efficiency can be proved only testing it in real market conditions, so I will carry out a pilot research to evaluate efficiency of suggested method. For the pilot research it is not important which stocks and indexes will be selected for analysis, so the main factor choosing them was sufficiency of historical data. So I will analyse 3 indexes: Dow Jones Industrial Average (Dow Jones); NASDAQ Composite (NASDAQ); S&P 500 (S&P); and seven company's stocks: Alcoa Inc. (AA); Boeing Company (BA); Caterpillar, Inc. (CAT); E. I. du Pont de Nemours and Company (DD); General Electric Company (GE); International Business Machines (IBM); Coca-Cola Company (KO).

4.1. Parameters of the empirical study

Starting the analysis it is necessary to decide what period length time series will be used. Aiming to evaluate not only actual data, but also long term stock market tendencies, I decided to use wide range of period (time series step) lengths: 1, 2, 3, 4, 5, 10, 20, 40, 60, 90, 120, 180, 240, 360, 480, 720, 960, 1200, 1500 and 1800 trading days.

Separate time series analysis and stock return forecasting is made using single moving average (SMA) and weighted moving average (WMA).

Single moving average is calculated using formula 5:

$$X_{t+1}^{k} = \frac{X_{t} + X_{t-1} + X_{t-2}}{3}, \qquad (5)$$

Weighted moving average is calculated using formula 6:

$$X_{t+1}^{k} = 0{,}5 \times X_{t} + 0{,}3 \times X_{t-1} + 0{,}2 \times X_{t-2}, \quad (6)$$

Mean square error for each of analysed time series is calculated evaluating square errors for the period of last 1800 trading days (the period equal to the longest period of time series analysed).

As a degree, used to enlarge the weight of the most accurate forecast in the integrated forecast, "n" in the analysis will be tested 1, 2 and 3.

The input of the analysis is historical data of daily stock prices and index values. The data analysis period was selected according to the sufficiency of historical data. The analysed time series have periods from 1 to 1800 trading days, so the latest 9000 periods were used for analysis and evaluation of data, which are necessary for forecasts integration. All the rest period was used for testing efficiency of the method. The number of tests made to evaluate forecasting efficiency for each index or stock is showed in table 1:

Table 1. Forecasting efficiency testing periods

Stock/Index	*Number of tests*	*Testing period*
Dow Jones	11761	1964–2011
NASDAQ	1264	2006–2011
S&P	6544	1985–2011
AA	3527	1997–2011
BA	3528	1997–2011
CAT	3528	1997–2011
DD	3527	1997–2011
GE	3527	1997–2011
IBM	3526	1997–2011
KO	3528	1997–2011

Table 1 shows that the most historical data for analysis had Dow Jones index, which allowed testing proposed method in period 1964–2011. So, evaluating efficiency of proposed forecasts integration method I will pay more attention analysing its accuracy forecasting Dow Jones index changes.

4.2. Results evaluation

To evaluate the accuracy of proposed forecasts integration method we must have a benchmark for comparison. In this analysis as a benchmark will be used the most accurate from non-integrated forecasts – one trading day period length time series forecast.

The efficiency of proposed method to improve forecasting accuracy is evaluated comprising mean square error using proposed forecasts integration method to mean square error of one trading day period length time series forecasts for all the testing period. The results of the analysis we can see at Table 2 and Table 3.

As we can see from Table 2 and Table 3, proposed method of integrating different period time series forecasts improves prediction accuracy. The most efficient integration is when "n" in formula 4 is equal to 2. Integrating single moving average forecasts decreased mean square error on an average 17.21 %, weighted moving average – 22.46 %.

We can also see that index forecasts integration has gained better results than stock. Considering the same number of tests (3528) S&P and Dow Jones MSE decreased more than in full analysed period, so the better efficiency of the method could be explained by the fact that indexes are more diversified than individual stocks.

The effect and benefit of integration we can also see in the histogram (Fig. 2), which illustrates that little forecasting errors were more usual in case of integrated forecast, however it didn't ensure avoiding big forecasting errors (10 and more percents).

Table 2. Efficiency integrating single moving average forecasts

	Dow Jones	*Nasdaq*	*S&P*	*AA*	*BA*	*CAT*	*DD*	*GE*	*IBM*	*KO*
MSE change (n=1)	-2.18 %	-9.37 %	-5.93 %	4.90 %	4.86 %	1.41 %	3.00 %	3.11 %	-2.90 %	-1.90 %
MSE change (n=2)	-16.51 %	-20.33 %	-18.14 %	-16.41 %	-15.25 %	-16.43 %	-17.47 %	-17.07 %	-17.51 %	-16.96 %
MSE change (n=3)	-10.42 %	-15.03 %	-15.30 %	-10.83 %	-10.79 %	-11.06 %	-12.16 %	-12.05 %	-12.61 %	-10.91 %

Table 3. Efficiency integrating weighted moving average forecasts

	Dow Jones	*Nasdaq*	*S&P*	*AA*	*BA*	*CAT*	*DD*	*GE*	*IBM*	*KO*
MSE change (n=1)	-10.32 %	-18.08 %	-13.98 %	-3.47 %	-3.69 %	-7.36 %	-5.59 %	-5.31 %	-10.74 %	-9.35 %
MSE change (n=2)	-21.30 %	-26.28 %	-24.32 %	-21.36 %	-20.54 %	-21.61 %	-22.70 %	-22.06 %	-22.70 %	-21.74 %
MSE change (n=3)	-13.09 %	-18.89 %	-16.10 %	-13.65 %	-13.85 %	-14.01 %	-15.21 %	-14.93 %	-15.76 %	-13.74 %

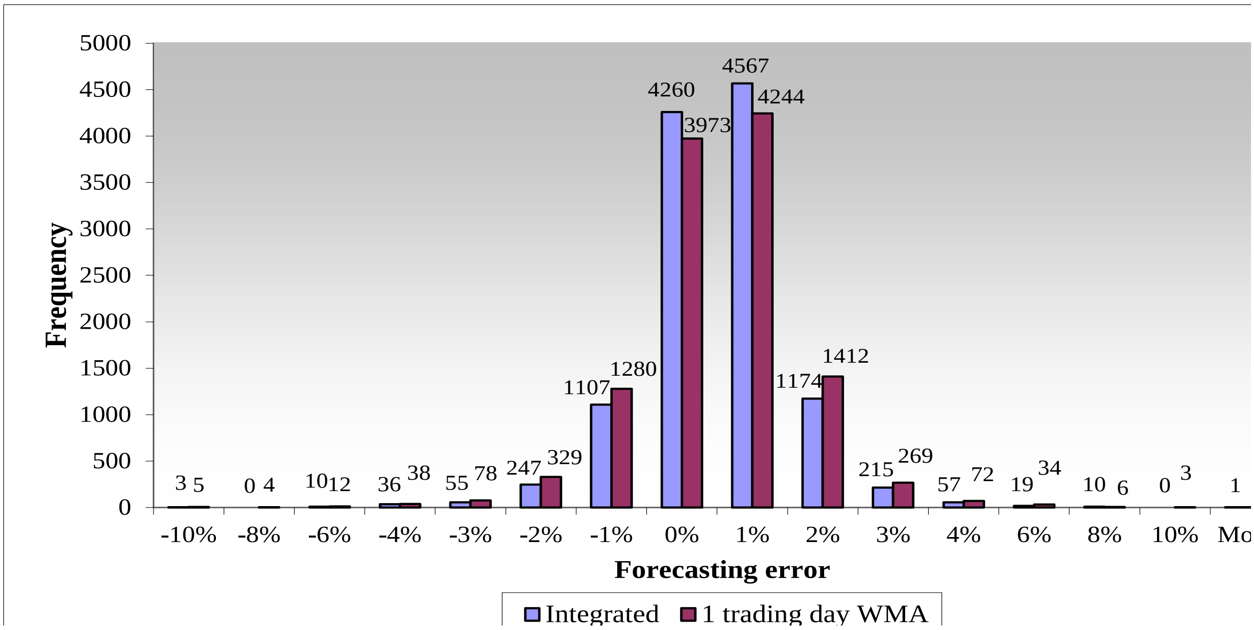

Fig.2. Forecasting errors distribution in case of Dow Jones index

It is important to mention, that in all 10 analysed cases, non-integrated 1 trading day period time series forecasts were more accurate using SMA, but the integrated forecasts were more accurate when using WMA. It means that integrating more accurate separate forecasts does not ensure better forecasting accuracy.

5. Conclusions

Summarizing theoretical analysis and pilot research results following conclusions are made the following conclusions should be made:

1. The theoretical analysis showed, that there are many stock return forecasting methods, forecasts integration topic is relevant and widely analysed in scientific information sources, however most of the scientists analyses separate forecasting methods not forecasts integration.
2. Separate forecasts integration topic was analysed by Nenortaite and Simutis (2006), Afolabi and Olude (2007), however Afolabi and Olude proposed HCSOM may not reach the best forecasting accuracy, because it uses only best neurons (in each case forecasts), and fully eliminates others, which can also be useful in integration.
3. Aiming to integrate forecasts, obtained using different forecasting methods, in the article was proposed an integration method based on past periods forecasting accuracy.
4. To evaluate the efficiency of proposed method in the article was carried out a pilot empirical study and proposed method was tested integrating different period time series forecasts made using SMA and WMA methods.
5. The results of empirical study showed, that the most efficient integration (the best forecasts accuracy) is gained using squared mean square error ("n" is equal to 2 in formula 4).
6. Comparing to one trading day period time series forecasts proposed forecasts integration method has decreased mean square error in case of SMA on an average 17.21 %, in case of WMA – on an average 22.46 %, however it did not ensure complete elimination of big forecasting errors.
7. One trading day period time series forecasts were more accurate using SMA than using WMA, but integrated forecasts are more accurate integrating WMA forecasts. It means that integrating more accurate separate forecasts does not ensure better forecasts accuracy and indirectly proves that HCSOM may not reach best results analysing only the best neurons (forecasts).
8. Proposed method is based on past periods prediction accuracy, so it can be used to integrate forecasts obtained with all available for investor prediction methods and programs which allow checking historical forecasting accuracy.

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