Model for sequential dynamic competition between random investment portfolios and portfolios selected by collective expert opinions

Angel Marchev, Jr.[1]

"The future is something which everyone reaches at the rate of sixty minutes an hour, whatever he does, whoever he is."
--C. S. Lewis

Abstract: This paper discusses the issue of market efficiency and proposes an approach for its empirical testing. The essence of the methodology is comparing expert opinions with randomly selected portfolios and implementing all the good practices of Delphi method for conducting an expert survey. The proposed approach also shares some similarities with the idea of prediction markets. The approach is yet to be validated empirically.

Keywords: Efficient market hypothesis, Online expert opinion survey, Delphi approach, Collective intelligence
JEL: G11, G14, C83

1. Research formulation

There is a prolonged international and interdisciplinary dispute on the topic of financial market efficiency. Ever since the financial markets emerged as the favorite destination for trading risk capital, scholars begun to speculate on market predictability. Starting the twentieth century was the remarkable but non-honored thesis of Louis Bachelier (Bernstein 1998) which raised the question whether the "past, present or even the discounted future events" reflected in the market price, show relation to the price change (Bachelier 1900). After him there was hardly a single decade in which the concept of efficient market hasn't been elaborated upon (Dimson et al. 1998).

In one of the founding theories of modern investment science Sir Maurice Kendall has stated that "in series of prices … the random changes … are so large as

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to swamp any systematic effect which may be present. The data [behaves] almost like wandering series" (Kendall 1953). Kendall shows that the probability of a given stock (or commodity) price to rise is equal to the probability to fall.

The biggest names after him to build on his ground work are Eugene Fama and Burton Malkiel – pioneers of the Random Walk Hypothesis, and the closely related Efficient-market hypothesis.

The free market is a social phenomenon which means it is subjective in nature, depending on the subjective decisions of all market participants. The random walk hypothesis states that because of the complexity of the market, the prices follow a random walk trajectory where the changes in future and the past states are independent from change in the current state so much that the price movement of a single stock is unpredictable (Malkiel 1973).

The efficient market hypothesis states that due to the information rich environment in which every investor makes decisions the current market stock price already reflects all known information defined as a set of past, present and (expectations for) future events and thus no one could utilize unique knowledge to profit from it (Fama 1965). The hypothesis was proposed in the 1960's and even if it has been partially correct then it surely must be much more so now with the modern communication and IT capabilities.

On one hand famous researchers such as Maurice Kendall, Burton Malkiel and Eugene Fama have studied the properties of financial time series with the general idea that the phenomenon financial market is principally unpredictable. The best suggestion for the investor in such information-rich environment is to invest in randomly selected wide portfolio and not to follow any analysis and forecasting. "Taken to its logical extreme," says Malkiel "[the theory] means that a blindfolded monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by the experts" (Malkiel 1973).

Of course on the other hand the notion that there could be no methodology for predicting financial markets objects most of the theoreticians and practitioners in the field of financial investments. There are enough opposing texts (see for example Lo et al. 1999, Dorsey 2003, Lo 2004) to justify the ever-springing theoretical and empirical tests of market efficiency. Looking through an alchemist eyes the topic has become the Philosopher's stone of investment theory.

In this paper the issue of market efficiency is treated unprejudiced and neutral following the epistemological principals of empiricism. The proposed approach for market efficiency testing is as much a methodology as it is an experiment proposition. Its validation with real life data is yet to be conducted and so the author has not yet formed conclusive opinion on the topic.

2. "Dartboard contest" of Wall Street Journal

For the last several decades numerous tests of market efficiency have been conducted – both scientifically sophisticated and more wide-public oriented with the Wall-Street Journal Dartboard Contest being the most outreaching and well commented. Starting in October 1988 it had run for fourteen years while the rules underwent only slight changes. Every month each of four "professionals" selected one long or short position for the next six months. The professional portfolio competed against a portfolio of four positions selected randomly by throwing a dart. The selected security had to comply with limitations on market capitalization, average daily volume, minimal price and market listing. Dow Jones Industrial Average was used as a benchmark measuring the market return. After six months the active returns[2] of the professional and the random portfolios are compared.

By the end of the competition Dow Jones Industrial Average had an average rise of 5.6% over the time period. The professional portfolios had an average of 10.2% investment gain (4.6% active return) while the random portfolios had 3.5% average gain (-2.1% active return) (Jasen 2002).

The most critical question to the competition (which is also topical for the current research) is whether the success of the professionals was self-inclined (Rasp et al. 2003)? Have their professional publicly stated opinion inclined the investors to trade along the professional selections[3] and thus drifting the market in gaining way?

Other major drawbacks of the procedure include:

- Very limited number instances (realizations) of expert opinions.
- Very limited number (only four) of instances (realizations) of randomness against which the expert opinion are confronted for a given time period.
- There were no weights in the random selections nor there were in the expert predictions. The portfolios were not intra-structured and optimized.
- The respective contests are analyzed separately, so there is no way to approximate any reasonable conclusion within the given time period.
- The pace of the experiment was very slow – only 48 seeds per year, six months for each contest.
- Relatively small number of securities complied with the limitations

Any sensible analysis within the above-mentioned drawbacks would have to be made post-factum after decades of experimentation and still would not be soundly proven. This is the reason why they had to analyze the results with some significance only after fourteen years of competition (142 six-month contests) have past.

[2] Comparing the portfolio return with the market return
[3] Buy their long positions and sell their short positions

Although non–scientific in essence, the Dartboard competition has introduced an innovative way to test market efficiency by comparing expert predictions with random selections.

3. Delphi method for processing expert opinions

The method is developed by Project RAND in the 1960s (Jantsch 1967). It is a systematic rational method for collective expert opinion, while avoiding unwanted effects of mutual influence among the experts. The key features are that every expert opinion is anonymized by the researcher and the various expert opinions are accumulated in a certain manner so that a unified and objectified opinion of expert group is drawn. The process is known also as knowledge extraction since it makes use of the unique experience, information and insights of the expert.

Delphi method used for predictions does not require the assumption of the Bernoulli hypothesis for perseverance of the historical conditions (Bernoulli 1713). The method is used when the quantitative methods are inapplicable i.e. unstudied, highly uncertain and complex phenomena.

In its original version the method was devised for predicting the moment of occurring of a certain event. In later uses another version of the method was also developed inquiring “what would be the value of a given measurable indicator at a given future point of time”.

The use of several repeating rounds of survey with feedback from the previous round achieves higher degree of consent among the experts which additionally could be measured by Kendall's coefficient of concordance. Other additions to the method may include evaluating the accuracy of each expert between rounds and weighting his/her opinion in the following round by some correction coefficient.

When applied for prediction of dynamical social phenomena such as stock markets, Delphi method could produce additional features:

- The collected data could be used for estimation of market expectations.
- If publicized, the results may vary the course of the market since the investors basically trade on their estimation of the market expectation. This would mean that simply by publicizing the results, they may become more accurate.

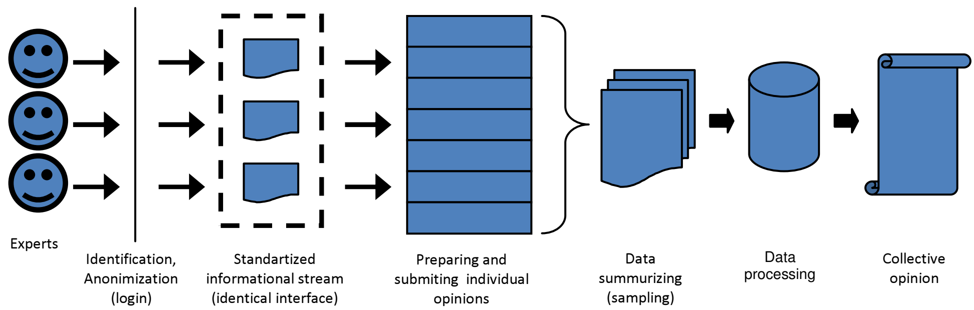
Introduction of the Internet has presented new opportunity for collecting and upgrading survey techniques (Harizanova et al. 2009). There are developments of the method in at least two directions – electronic Delphi approach and prediction markets.

The electronic Delphi approach (e-Delphi or Online Delphi) is in essence an electronic forum with non-stop, repeating anonymized survey of many experts so that there is a constant stream of new objectified opinions on the topic.

Online Delphi system introduces so many opportunities and changes to the method that it actually becomes a new methodology of system for online processing of expert opinions. Such system has a lot of advantages and solves (at least partially) most of the typical problems of Delphi approach:

- The communication with the experts is fast – sluggish communication has invariably been the biggest setback in an offline survey.
- The experts are presented with equal informational conditions when they submit their opinions.
- The results could be updated dynamically and presented instantly. An adapting mechanism for weighting the expert opinions may be incorporated dynamically.
- There is no need to follow a rhythmic schedule for the consecutive rounds of survey – every expert could log on and present opinion at own pace. The feeling of not being hustled additionally encourages the experts to participate.

Figure 1. Online system for processing expert opinions



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Prediction markets are a concept combining the idea of e-Delphi with stock-market-like trading of statements. Participants use virtual money to trade the statement as if it was a security on a free market. Typically there is some sort of material award to encourage participation but also to hold off any undisciplined behavior/opinions. And typically there is an end date for a given statement to be traded. The current market quote of the traded statement is the market estimation for its truthfulness. Prediction markets conceptually work not because of expert participants but because the law of large numbers. Since the traded statements are of social (non-natural) essence, the assumption is that large numbers of the subjective opinions reflect wide range of more diverse and more significant information.

4. Proposition for method of testing market efficiency by processing expert predictions

The current paper describes the principal model of a version of online system for processing expert opinions (predictions in principle). Such a research has been a long coming project of the author (Marchev Jr. 2004a, Marchev Jr. 2004b, Lomev et al. 2005) and it could only be executed in a fast-communication environment with easily accessed information streams. As an additional research objective it would be interesting to test the efficiency of an emerging market (Takala 1997) such as Bulgarian Stock Exchange. The effects from running such a competition in a small market are also of interest. The methodology of the research has several important features:

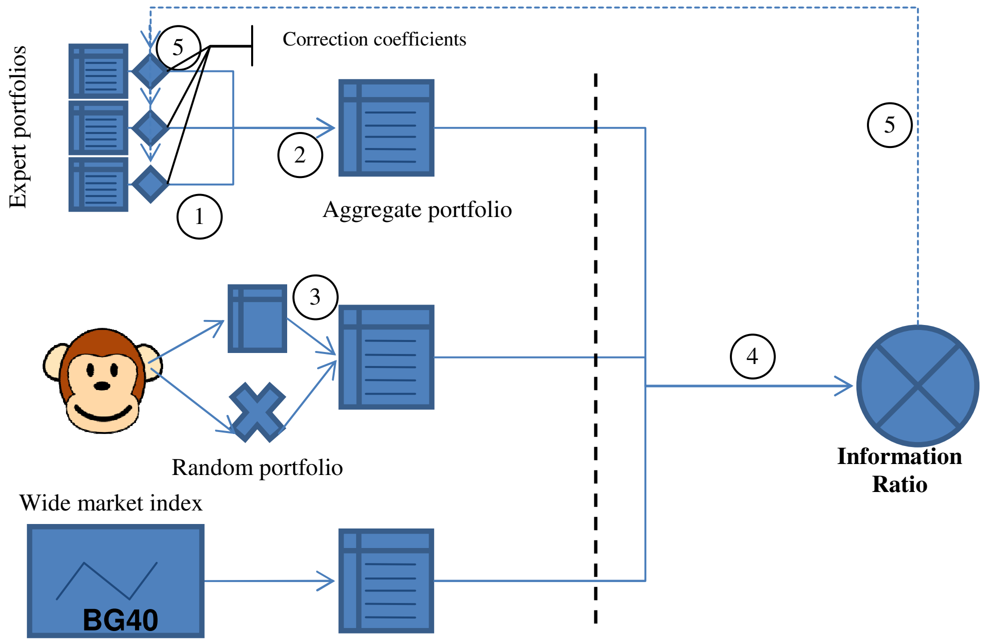
- It is conducted online (Internet), following the principles of Delphi approach such as expert anonymity, unified information stream, ability to exchange supporting arguments among experts and collecting all expert prediction portfolios in one collective portfolio.
- Every expert is put in an identical information environment, after logging in the online system. Firstly there is a standard interface page with useful information about the stock market, stocks, current news, etc. Secondly taking into account the information rich environment of the Internet and the information processing capacity of a human being, one could assume that everyone has access to incomprehensive (leaning towards infinite) volume of useful information.
- Parallel to submitting predictions, the experts may choose to leave argumentation in the electronic forum. The forum should be moderated towards anonymizing the experts' arguments. This action is reflecting one of the founding concepts of Delphi method – anonymous feedback.
- The main innovation is that the model is designed to render dynamically collected expert opinions (this has always been the challenge with applying Delphi method for forecasting financial markets) (Marchev Jr. 2004b).
- It presents the experts useful information even during the forecasting stage of the competition. When an expert submits his/her prediction portfolio, the current state of collective portfolio is available to him/her for analysis. An advantage for the expert is also that predictions could be submitted (and accessed) even when the stock market is closed for trading (much like a prediction market). These features are mainly aiming to encourage participation from the experts and present a possible solution of the problem with "Non-rhythmic" expert opinions (a typical issue with the Delphi approach).

The proposed methodology includes several steps (Fig. 2.):

1. Expert prediction submission.
2. Aggregating expert portfolios.
3. Generating random portfolio.

4. "Contest day".
5. Feedback.

Figure 2. Proposed methodology – main scheme



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5. Expert prediction submission

The experts submit their predictions for profitable investment portfolios for a future point of time – "contest day". There is a prediction window during which the expert predictions are collected for every "contest day". Each expert could submit "prediction portfolio" every day within the prediction window, once a day. All submitted prediction portfolios of an expert during the prediction window are kept and computed in an aggregate portfolio. Requirement for the expert to participate regularly may be imposed (e.g. at least once every 30 days).

The experts submit their "prediction portfolios", consisting of k positions each with respective weights, where k is the total number of positions traded on the market (or criteria for admission of positions may be used). For unwanted positions the weights are set to 0. Each portfolio has a nominal sum of S at submission. If the positions in a portfolio sum up to less than S, the residual is assumed a cash position

C_j. The cash position cannot be less than 0 – no borrowing allowed (1). Short positions are also possible[4], accounting the fact that the invested amount in short positions is "blocked" (counted as positive) – no margin account. The market is assumed "frictionless" e.g. no transaction costs, inflation, taxes, interest on cash positions etc. are computed.

$$P_j(t) = \sum_{i=1}^{k} w_{ij}(t) + C_j(t) = S \qquad (1)$$

where :

j - serial number of expert

i - serial number of position

k - total number of possible non-cash positions

t - day of the prediction (within the prediction window)

$P_j(t)$*- value of prediction portfolio of expert j, submitted at the moment t*

$w_{ij}(t)$ *- allocated sum of position i in the portfolio of expert j, submitted at the moment t*

$C_j(t)$*- value of cash position of expert j, submitted at the moment t*

S - nominal investment amount

In its essence equation (1) is the typical way to calculate the value of a portfolio. What is important here is that the cash position C_j acts as a plug variable to sum the value of the portfolio to the investment amount *S*.

6. Expert prediction submission

This phase includes two stages – computing each expert's aggregate portfolio and collecting all aggregate portfolios in a collective portfolio. Actually the operations at this phase are done not only at the end of the contest, but also dynamically throughout the contest so the information about the current state of the collective portfolio is available. Being available means that every expert could see it since it is a valuable piece of information not only for the contest itself, but also for their real life work. So this is the motivational mechanism for participation – if an expert would like to see the current state of the collective portfolio (which reflects the expectations of all other experts), he/she must submit a prediction portfolio.

All prediction portfolios of an expert are combined in an "aggregate portfolio" by arithmetic averaging of respective positions of all prediction portfolios (2).

There is an incorporated mechanism for correcting (weighting) the expert opinions as a function of time of submitting each prediction with the newer having bigger impact on the final collective portfolio. So the aggregate positions are

[4] Short positions on Bulgarian Stock Exchange are not used in practice due to overregulation

corrected by correction factors (3). The correction factor uses exponential weighting (4).

$$\overline{w_{ij}(m)} = \frac{\sum_{1}^{m} w_{ij}(t)}{m} \tag{2}$$

where :

m - serial number of portfolio, submitted within the current prediction window

$\overline{w_{ij}(m)}$ *- value of aggregate position i in portfolio number m, submitted by expert j*

Equation (2) is a simple arithmetic average of the prediction portfolios, submitted by one expert. The index *m* here denotes the day (out of the prediction window) on which the expert submits a prediction portfolio. Note that since an expert could submit one prediction portfolio a day, the number of prediction portfolios by an expert cannot exceed the number of days in the prediction window i.e. $\{m\} \subseteq \{t\}$.

$$\overline{\overline{w_{ij}(t)}} = \frac{\sum_{t=1}^{n} \overline{w_{ij}(t)}.T(t)}{\sum_{1}^{t} T(t)} \tag{3}$$

where :

$\overline{\overline{w_{ij}(t)}}$*- corected value of aggregate position i in aggregate portfolio of expert j, at the moment t*

T(t) - correction factor for time at the moment t (see below)

It may seem that the correction for time of submission in equation (3) is done a bit too complicated and un-elegant, but it is needed to be such to have an important property – "rolling computation". It is meant that at the end of each day of the prediction window all of the submitted prediction portfolios are computed.

$$T(t) = \frac{2t}{2n + n(n-1)} \tag{4}$$

where :

t - serial number of the prediction day within the prediction window

n - total number of days in the prediction window

Equation (4) is derived from the general formula for linearly-weighted moving average. This is a necessary calculation since the predictions submitted earlier are reflecting less significant information than the predictions submitted later and are presumed less accurate.

The other stage of this phase of the contest is constructing a collective portfolio. This is done by averaging aggregate portfolios of all experts (5).

$$P_g = \sum_{i=1}^{k} w_i + C_g = S \tag{5}$$

where :

P_g *- value of collective portfolio*

w_i *- value of non-cash position i in the collective portfolio* P_g

C_g *- value of cash position in portfolio* P_g

Similarly to (1) the cash position of the collective portfolio is summing up the value of the portfolio to the investment amount *S*. The value of a non-cash position w_i in the collective portfolio (6) is an average of the current values of the corresponding positions, weighted by a correction factor $I_j(v)$. Using the equation (6) w_i could be computed after every day of the prediction window, thus making it available for the experts.

$$w_i(t) = \sum_{j=1}^{J} \frac{\overline{\overline{w_{ij}(t)}}}{j} . I_j(v) \tag{6}$$

where :

v - serial number of the current prediction window

$I_j(v)$ *- correction for expert accuracy for current prediction window v, where* $I_j(1)=1$

The correction factor $I_j(v)$ is a correction for the accuracy of every expert. Such correction is computed on the basis of the prediction accuracy of the expert from the previous prediction window. For the initial contest the value of the correction is 1 (i.e. no correction). The correction for accuracy is explained further in the paper.

7. Generating random portfolio

A "random portfolio" is selected and structured using random number generators. There is an important discussion on what sort of random generators should be used while testing market efficiency. On one hand there are the pseudo-random number generators – deterministic software producing chaotic features in sequences of numbers. On the other hand there are the real-random number generators – typically hardware device digitizing stochastic properties in sequences of numbers through some physical phenomena such as atmospheric noise or radioactive decay[5].

What is important to understand for the purpose of this paper is that generating the random portfolios is not a mere simulation but rather it is close to a game of chance. So for the current paper the most clear-cut and obvious approach is proposed. In honor of one of the most famous quote of Burton Malkiel[6] and in attempt to be as genuine as possible, real- random number generators such as darts and dice are used. Of course the author is aware that more advanced real-random number generators could be used. For a non-conclusive list of real-random number generators see (Marchev Jr. 2008).

The random portfolio is generated in two stages:

1. Random selection of fixed number of positions (at least 10) by blindfolded throwing darts at a newspaper's financial page / printed list of the positions (or other means of random selection out of a list of the positions).
2. Random definition of weight for each position using dice. Preferably regular shaped dice (platonic solids) such as icosahedron or dodecahedron but also pair of identical pentagonal trapezohedron (percentile dice) is an option since they will produce a random number from 0 to 99. Ideal would be a pair of icosahedrons with repeated sides. (0 through 9 or 10 through 90 repeated twice on a die). In the case of the latter two see (7). The aim is to incorporate more degrees of freedom, effectively meaning more „un-round" numbers. As well as introducing more instances of randomness to the portfolio[7].

[5] See for a brief introduction: http://www.random.org/randomness/

[6] See part 1 of the current paper

[7] It is easily seen that the simpler the dice the less degrees of freedom is introduced by one toss. The simplest of dice – two-sided die (i.e. a fair coin) would only produce one degree of freedom, so for a portfolio of 10 positions the weights of would be divisible to 5%.

Figure 3. Ten sided dice, pentagonal trapezohedrons

Source: http://en.wikipedia.org/wiki/File:DnD_Dice_Set.jpg

$$w_i = \frac{d_i + 1}{\sum_{1}^{i}(d_i + 1)}.S \tag{7}$$

where :

i - serial number for postion

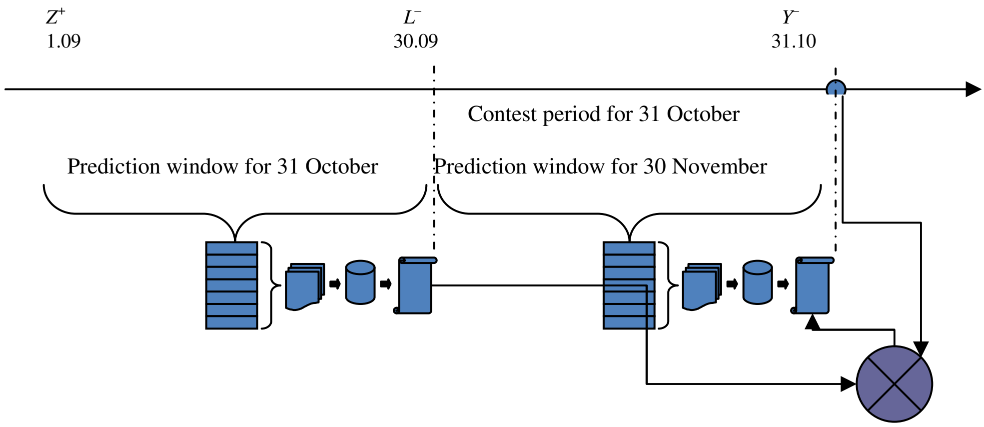
d_i *- random dwo-digit integer for position i*

w_i *- value of position i*

8. "Contest day"

The contest day (Y^{-}) is on the last working day of a month. The prediction window starts on the first day (Z^{+}) and ends on the last day (L^{-}) of the month prior to the month of the "contest day". The month which ends with the "contest day" is called "contest period". There is minimum one month and maximum two months of uncertainty for the experts when they prepare their predictions. All stock market values used in the research should be adjusted for splits and dividends.

Figure 4. Timeline example of the prediction window



Source: own creation

A market index for the same stock market is used as a benchmark for measuring portfolios' progress. Ideally it should be a wide market index with weighted-average of all securities traded on the market.

On "contest day" the two portfolios are competed to each other on the basis of a modified information ratio. Modified information ratio is accounting for the active return of the portfolios and variation of the historical prices which is a common measure for risk.

The portfolios are evaluated on real market quotes, considering the opening prices (L^+) on the first working day after the end of the prediction window and the closing prices (Y^-) on contest day. Rules for inputting missing values in the financial time series are necessary (8).

$$R_g = \frac{P_g(Y^-) - P_g(L^+)}{P_g(L^+)} \tag{8}$$

where :

R_g - *historic return of collective portfolio for the contest period*

Besides the value of on the contest day for the computation of equation (8) is needed the value on the opening of first working day of the contest period L^+. Note that there is a maximum of 23 working days in the contest period (with real-life stock market quotes), while there could be up to 31 days in the prediction window (on which experts could submit predictions).

$$E_g = \frac{R_g - R_M}{\delta_{R_g(t)}} \tag{9}$$

where :

E_g *- modified information ratio*

R_M *- historic return of market index for the contest period*

$R_g(t)$ *- daily dynamic return of aggregate portfolio, durring the contest period*

$\delta_{R_g(t)}$ *- tracking error of daily returns of collective portfolio, see below*

The information ratio (9) is actually a simplified version with only two values taken for calculation of the return.

$$\delta_{R_g(t)} = \sqrt{\frac{\sum_{1}^{h}(R_g(t) - R_M(t))^2}{h-1}} \tag{10}$$

where :

h - number of days in contest period

The tracking error (10) uses connotation of *t* as the serial number of a working day form the contest period.

$$R_g(t) = \frac{P_g(t)}{P_g(t-1)} - 1 \tag{11}$$

The dynamic daily return of the market index is calculated exactly the same way as for the collective portfolio, shown in equation (11).

9. "Contest day" consequences.

After the contest is over the results are not only used for analysis but also serve as correction factors for the further contests. Already explained was the correction for time of submission. The incorporated mechanism for correcting (weighting) the expert opinions as a function of accuracy was also mentioned. The principle is that the better predictors from the previous contest have bigger impact on the final collective portfolio (12).

$$I_j(v) = (1 + E_j(v-1)).A(v-1) \tag{12}$$

where :

$E_j(v)$ *- modified information ratio of expert j for prediction window v*

$A(v)$*- correction from adaptation algorithm,* $A(1) = 1$

Again for the computation of the correction factor for accuracy the modified information ratio is used (13). This time it is calculated for every individual expert. Since the results of the previous prediction window are ready at about the end of the current prediction window, the correction for accuracy is assumed to its last computed value until the new value replaces it.

Both of the above-mentioned correction mechanisms (for time of submission and for expert accuracy) and the model as a general introduce inherent systematic errors for which an adapting mechanism is proposed (e.g. stochastic approximation) (12), see fig. 5. The value for the initial contest of the adaptation correction is 1. Important remark is that the average corrections for accuracy and adaptation on all expert aggregate portfolios should be as close to 1 as possible.

$$E_j(v) = \frac{R_j - R_M}{\delta_{R_j(t)}} \tag{13}$$

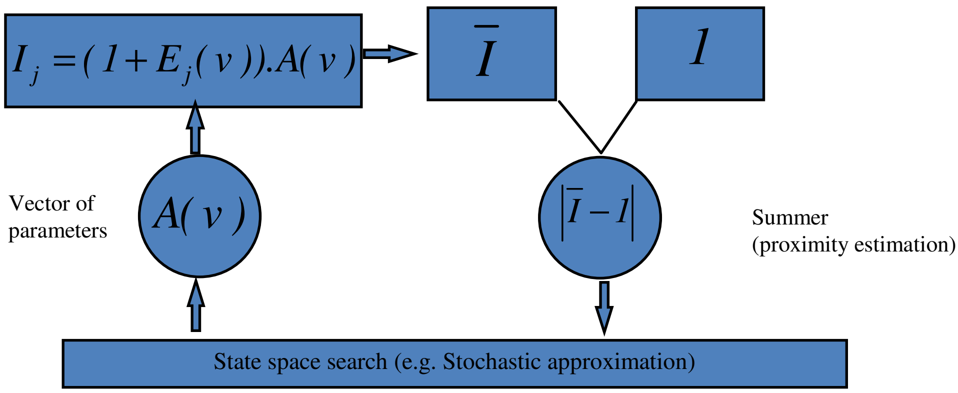
where :

R_j *- return on aggregate portfolio of expert j*

$\delta_{R_j(t)}$*- tracking error on daily return of aggregate portfolio of expert j*

All the requisite variables of equation (13) are computed exactly as for the collective portfolio from equations (8), (9), (10), (11).

Figure 5. Algorithm for computing the value of A



$$arg\ min_{A(v)} \left|\bar{I} - 1\right|$$

Source: own creation

The adapting algorithm uses the arithmetic average of the individual correction factors for accuracy $\bar{I}$ and compares it with the value of 1. Through iterative process is searched such value of *A(v)* for which the goal function $\left|\bar{I} - 1\right|$ is the closest to zero. The computed such value is included in the correction factor for each expert.

10. Empirical example

In the next few paragraphs there is an example of the implementation of the above-mentioned approach. The computations use historical data of four shares, listed on Bulgarian Stock Exchange and data of a major market index for a period of two months. Additionally the expert portfolios (opinions) are simulated using arbitrary and subjective opinion of three individuals. As much as the example is only for illustration purposes, it is not meant to be an empirical test of any sort. So the resulting numerical values of the variables are not at all important, but the whole demonstration of how the approach works. It is done mainly to satisfy a reviewer's request.

Assume there are three experts (Expert1, Expert2 and Expert3) who have submitted their prediction portfolios allocating 10000 EU to five positions (share A, share B, share C, share D and a cash position) as follows (see Table 1). In the table each row represents a prediction portfolio submitted by the corresponding expert on a given day of the forecast window. For example: on the first data row of the first section it is shown that Expert1 has submitted a prediction portfolio on the first day of the prediction window allocating 6549 EU for share A, 432 EU for share B, 414 EU for share C and 1956 EU for share D thus leaving 649 EU (out of the 10000 EU) in cash. The random portfolio is simulated using percentile dice and computed as in equation (7)

Table 1. Simulated prediction portfolios

Expert1					
Day of the prediction window	Allocation by position				
	A	B	C	D	Cash
1	6549	432	414	1956	649
7	1328	3124	3032	780	1737
12	810	2834	541	3286	2529
15	3277	1117	1807	812	2986
19	66	1513	2152	5365	904
26	2486	1431	1280	3866	938
29	373	565	3677	3718	1667
Expert2					
Day of the prediction window	Allocation by position				
	A	B	C	D	Cash
6	2206	2558	424	3245	1567
10	2094	2898	1863	2849	296
22	2549	1641	2791	755	2264
30	1548	742	2137	1646	3928
Expert3					
Day of the prediction window	Allocation by position				
	A	B	C	D	Cash
2	249	3320	3766	1881	784
14	216	3130	1648	3405	1600
16	1210	662	4660	1845	1623
19	983	4832	1751	1561	872
27	1758	2444	3179	2520	99
Random portfolio					
Day of the prediction window	Allocation by position				
	A	B	C	D	Cash
30	1304	174	1652	3043	3826

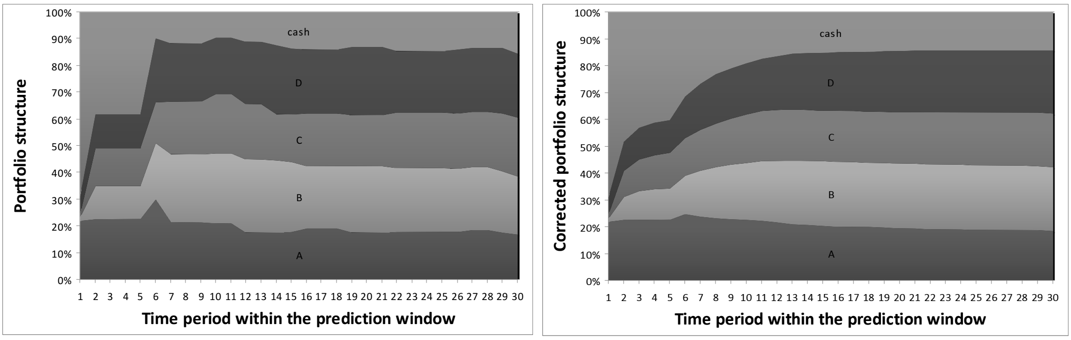
Source: own creation

Using these prediction portfolios the structure of the collective portfolio could be computed – as submitted as well corrected for day of submission (for graphical representation see fig. 6). The figure clearly shows the difference between the non-corrected and the corrected portfolio.

The next phase of the contest is to observe the dynamic of the portfolios (fig. 7) as well as their return on contest day (-7.2% for share A, -3.8% for share B, 4.2% for share C, 1.2% for share D and -1.2% for the market index).

Figure 6. Structure of the collective portfolio during the prediction window

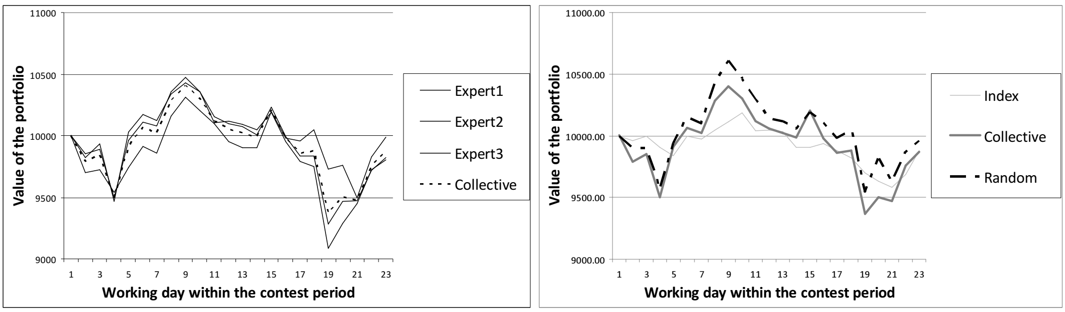
a) as submitted b) corrected for time of submission



Source: own creation

Figure 7. Dynamic daily value of the portfolios during the contest period

a) expert portfolios and collective portfolio, b) random and collective portfolios, market index



Source: own creation

The results of such simulation would be as shown in Table 2. The collective portfolio performed better than the index although still losing. The random portfolio (in this realization) was almost on par with the initial invested amount. The performance of Expert1 and Exper2 was worse than the performance of the market index. So their respective correction factors for the next prediction window would lessen the weight of their prediction in the collective portfolio. Just the opposite for Expert3 – the correction factor is above the value of 1. The whole adaptation correction factor is slightly below the value of one, correcting a systematic error of overvaluing the collective portfolio (possibly due to the decreasing values of the market index this contest period). And of course it should be reminded that this was only a simple example of the approach.

Table 2. Contest day results

	Expert1	Expert2	Expert3	Collective	Random
Value of the portfolio	9821	9841	10002	9888	10005
Value of the index	9881				
Return of the portfolio	-1.8%	-1.6%	0.0%	-1.1%	0.0%
Return of the index	-1.2%				
Information ratio	-18.9%	-14.2%	62.3%	2.9%	50.0%
Adaptive correction	0.911				
Correction for accuracy	0.739	0.782	1.479		

Source: own creation

11. Conclusions

Since it is only a proposition, the current research mostly raises questions:

1. Being able to see the predictions while predicting, do the experts make the market even more efficient?
2. Is it so on Bulgarian stock exchange, where the experts are relatively small number (and so everybody tend to believe a relatively small number of subjective opinions) and where the market is generally shallow (meaning easily manipulated) and underdeveloped (predictable)?
3. If the market follows the expert expectations, wouldn't it lead to degeneration of their predictions (due to multicolinearity)? Would the market become "sensible dependant on small changes in the initial values" (Lorentz 1993)?
4. Since the collective portfolio averages on many experts with many positions and comparing it to a random portfolio averaging even more positions, wouldn't the differences among the two portfolios and the market index be insignificant (due to regression to the mean)?

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