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Dissertation

Artificial Intelligence with Modern Portfolio Theory

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Abstract

This work is a research on a novel adaptive algorithm designed to produce assets allocation weights in a portfolio of assets for any desired moment in time. Using combination of Artificial Neural Networks, Evolutionary Programming and Modern Portfolio Theory, it is aimed to beat simple historical method for Optimal Risky Portfolio estimation and provide an investor with an edge in continuously changing financial environment.

Keywords: *Portfolio Theory, Investment Analysis, Assets Allocation, Neural Networks, Evolutionary Programming, Fund Management, Time Series Prediction*

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Chapter 1

Introduction

The idea underlying this project is to develop foundation for profitable trading system. During past years rapid developments in technology amazingly improved computer hardware speed and efficiency. This has not been left without attention to investors all over the world resulting in advanced developments in automatic trading systems.

To begin with, first trading systems emerged with first computers in early 1970's. Although this was a breakthrough, capabilities were not amazing because of slow speed of execution and small size of back-testing data set. During the next 30 years of computer revolution together with developments of the Internet network, trading became more efficient, available to larger groups of people - simply speaking, expanded amazingly. More members of stock exchange started trading on their own. Additionally, stock markets developed in many countries around the world. This created huge global network of participants. These days, tens of thousands of different assets are available to investors. They can choose whatever they like, limiting themselves to maximum risk which are willing to undertake.

These conditions forced traders to move from paper/telephone based trading to electronic, and NASDAQ exchange was a pioneer in this type of exchange. Electronic stock exchange again drastically reduced execution time to seconds allowing brokers to reduce their fees and lower spreads as transaction no longer required participation of broker, because client could post a trade straight into exchange. This improvement allowed to process more orders than anyone could ever imagine. Liquidity increased as a result. It was finally possible to profit from very small movements in asset price.

Combining both electronic exchange access and high computing speed, automated trading systems became very popular among market participants. Some of the systems profit from simple arbitrage - these are just real time algorithm which in a matter of milliseconds execute a trade which allow for small arbitrage profit. Biggest advantage of these algorithms is their broadness (they can simultaneously monitor thousands of assets) and speed as arbitrage opportunity may sometimes last only few seconds. These conditions became to difficult for human traders who have the ability to monitor only a few assets and execute trades very slow.

Therefore, as presented situation suggest, algorithmic trading is with no doubt future of the market. Soon, those who can program better strategy will be more valued than human traders, because better automated systems will allow institutions to gain the edge within competitors and will decide about overall success of the company.

To keep abreast of times, this work has been prepared to examine how an algorithm based on recent advancements in computer science would perform. Combining Neural Networks with Evolutionary Programming and processing results with Modern Portfolio Theory model is expected to provide superior profit. Will this be a case - the research will show.

1.1 Motivation

This work proposes full framework for analyzing investment in any desired assets. Investor managing a portfolio is always faced with the problem of best assets allocation. Which assets should be exposed more and which less from the others? Often this decision is made based on the analysis of reports produced by analysts. These reports are the results of work which often tries to predict future behavior of analyzed time series. By doing so, they base their predictions on personal experience and expertise, economic indicators (i.e. GDP, Interest Rates, Unemployment Rate, T-Bills) or market factors (i.e. past performance, closing price, volatility, futures prices). This is with no doubt, very difficult task.

Therefore, the aim of this work is to develop an algorithm, which will automate process of portfolio optimization. Ideally, when using the algorithm, one would like to be able to provide input data and obtain output indicating where and how much to invest. This feature would make it similar to a human expert. There exists a group of algorithms called Artificial Neural Networks (ANN), which can work in a way just described. Applying set of data series as an input, ANN is expected to produce good prediction. Analogically, analyst who analyzes some data provide conclusions from them.

Because of Neural Networks ability to approximate nonlinear functions, it is expected that estimation of Risk and Returns will be better than when using simple estimators. To prove this statement, obtained results will be compared against other estimation methods (i.e. simple average and standard deviation). There is a number of parameters to tune up whole algorithm, but this is very wide subject and details will be described fully in chapter 5.

Finally, the main goal of the project is to produce and analyze algorithm which will at any time provide an answer to the following questions:

- *What is the best allocation of assets at the moment subject to changes in market conditions? (Word "best" is meant to be the highest return and lowest risk)*
- *How to re-balance the portfolio so it is always optimal.*

To accomplish this goal, automated algorithm will be prepared and further tested on real life data. To set up practical model, portfolio of seven major stock index futures will be examined: CAC40, DAX, FTSE100, Nasdaq, Nikkei, S&P500, WIG20. These have been chosen, because economic data for countries they are traded in are widely available and if obtained results will be promising, they could be tested in real life investing.

1.2 Project structure

To summarize, the work is organized as follows:

- Chapter 2 will outline past research done in portfolio optimization, problems that exist with currently known methods and direction which can be followed to address some of the problems.
- Chapter 3 will describe the theory hidden behind used algorithms: Neural Networks, Evolutionary Programming, Modern Portfolio Theory and also some additional helpful functions, which are required to solve some encountered problems, i.e. data re-scaling, output creation, etc.
- Chapter 4 will provide a description of data that has been used for the purpose of the project. Input and output together with descriptive statistics will be briefly analyzed.
- Chapter 5 contains analysis of the results obtained from analyzed data. Here, results for different set-up of parameters will be presented and analyzed to provide solid conclusions and possibly build a theory based on the results. Three types of research will be performed - pure standard Markowitz approach using simple average and standard deviation approach, pure Neural Network prediction and combination of both.
- Chapter 6, finally, will gather all conclusions made during the previous chapters and will be a summary of the work conducted. Possible future ideas for improvement will also be presented.

Chapter 2

Literature review

Finding an Optimal Portfolio which maximizes return and minimizes risk of an investment is a difficult task. Before Markowitz (1952) proposed an algorithm which produces good approximation for a collection of assets, investors were assessing stocks individually, ignoring influence of each other when combined together. His work proved mathematically, that investors should focus on the overall risk and reward of portfolio. In 1958 model has been expanded by Tobin (1958) to make use of leverage, by introducing risk free rate. Sharpe (1964) based on the work of his predecessors formalized CAPM, proving that market portfolio lies on efficient frontier. Established theory was very promising in theoretical conditions with many simplifications, but in its simplest form, lacks robustness and its performance in real life conditions is at least insufficient. This has been summarized by Michaud (1998):

"Although Markowitz efficiency is a convenient and useful theoretical framework for portfolio optimality, in practice it is an error prone procedure that often results in error maximized and investment irrelevant portfolios."

First of all, this model is very unstable: only small changes in Expected Returns and/or Variance might result in large changes in weights for assets allocation. Additionally, difficult estimation process of parameters rarely produce real value, giving only approximation. Number of studies confirmed these phenomena, to mention just two i.e. Broadie (1993) conducted research on influence of errors on the efficient frontier. Chopra (1993) investigated turnover of portfolio as an error of the estimation. Another difficulty with Mean/Variance portfolio optimization method is, that the model is static. According to Scruggs (2005), Variance of an asset changes over time, thus to be able to fully use Markovitz algorithm as an investment strategy, one should be able to run the algorithm continuously. This will allow adaptation to changing conditions and produce optimal asset allocation for portfolio at any time. Finally, model in its simplest form, produces results which are solely based on past performance which may not, and often is not, appropriate to the future.

To address above problems, the following work will be performed. Whole project is based on an idea of utilizing Artificial intelligence (AI) algorithms to overcome described obstacles. Two of them: Artificial Neural Networks (ANN) and Evolutionary Programming (EP) have been put into consideration as constituents of algorithm developed by Radlak (2007), which will be the basis for calculations.

Artificial Neural Network is a model which maps structure of biological human brain into mathematical equations. The idea was to develop "thinking" machine, but the result was very far from desired. ANN are not able to make decisions, but they can approximate, to some extent, any nonlinear function as proved by Hornik et al. (1989). In other words, this model can learn to produce desired output for a given input without knowing analytical relationship between them. In case of time series, we can train Neural Network to predict future of a series, if only training is appropriately organized.

Therefore, ANNs have many applications these days and finance is one of them. Especially with time series prediction which has been broadly studied, i.e. Haykin (2005) provided comprehensive description from engineering perspective. His work was not the only one and was also conducted by i.e.: Cottrell et al. (1995), Lendasse et al. (2000), McNeils (2005), West et al. (2005), McAdam & McNeils (2005). There is also vast universe of Neural Network algorithms, i.e. Feed-Forward, Radial Basis, Kohonen Self-organizing Network or Recurrent. Chapter 3 is devoted to describe specifics of algorithm used.

Another "natural" algorithm used for the purpose of this work is Evolutionary Programming (EP) based on Darwinian Evolution Theory as first proposed by Fogel et al. (1966). It is an optimization method which uses following genetic operators, known from biology: selection, mutation and crossover. Each solution in population of solutions is selected, crossed over and mutated in order to produce children. These offsprings compete between themselves. The fittest survive and is included in next generation for further reproduction until best solution is found.

Because of its properties, EP can be used to simulate evolution of ANNs. In this case, solution is a string (chromosome) of weights between neurons. Main goal is to find such set of weights, for which output produced by this Neural Network is closest to desired output (measured i.e. in terms of Root Mean Square Error). It is worth mentioning that combination of Neural Networks and Evolutionary Programming into hybrid, is able to adapt much better to the data than just pure back-propagation method Yao et al. (1999). The main advantage of EP in this case is that it searches for global solutions and avoid poor local minima. Therefore, it is expected that fittest ANNs will be able to produce accurate predictions, as used in this project.

This brief review shows that the problem with portfolio optimization indeed exists, but there are also tools available, which could solve the problems, or at least minimize their effects. Further chapters will provide detailed descriptions of how presented algorithms will be combined together into one working body. Therefore, whenever it will be appropriate and required, literature will be cited in the remaining chapters of this work.

Chapter 3

Methodology

Proposed algorithm is expected to produce predictions for desired time series. While designing it, following key requirements have been stated and were expected to be met:

- flexibility - there should be no constraints for the input size and characteristics - anything that is expected to be good input should be allowed for inclusion. Additionally, user should not be limited to what output can be produced and should be able to choose anything, that is required,
- adaptability - algorithm should be able to adopt quickly to very rapid changes in financial markets,
- stability - algorithm should produce stable output and be able to sustain high volatility periods in the markets,
- intuitivity - user should easily understand what is "inside" algorithm which at first sight looks like a "black-box" solution.

To fully understand the theory behind proposed algorithm, this chapter has been prepared to describe its building blocks. It is important to know how does it function - in detail. Only this will allow for proper and accurate use and informed decision making which hopefully will bring investor high returns on investments. Therefore, at first, each of the components will be described. Secondly, description of assembled algorithm will be performed to finally describe its all possibilities and real life applications.

Therefore, following sections will be organized as follows: at first, brief description of the whole system will be presented and pre-analysis algorithms used for dimension reduction will follow. In next section, concept of Neural Networks will be described in detail and overview of Evolutionary Programming will follow. Next, algorithm which will gather everything together into a working body will be introduced and application of Markowitz will be described. Finally, chapter will conclude with some minor issues, which were important for the functioning of the whole algorithm.

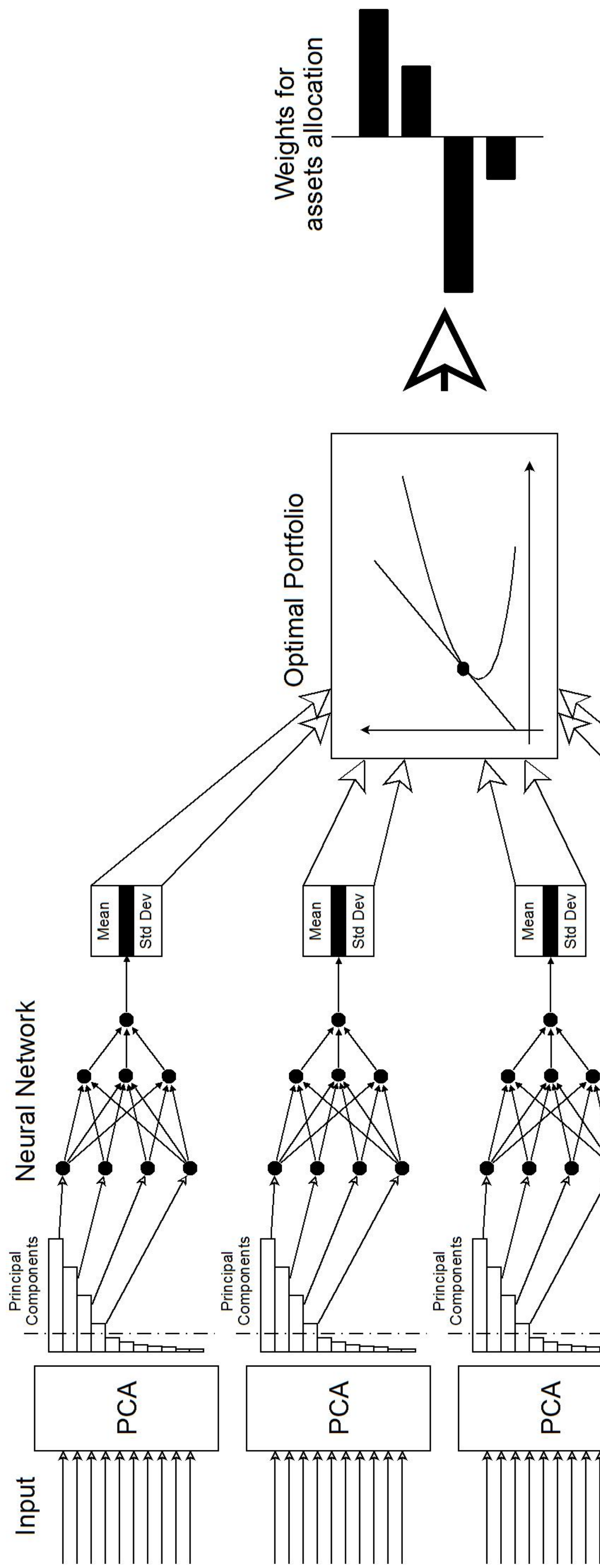


Figure 3.1: Structure of the whole algorithm

3.1 Whole system overview

Figure 3.1 presents key components of the whole system. As an output, one expects to obtain weights which will be used for assets allocation in portfolio. To achieve this, first, an input set has to be prepared. This should consists of time series which one expects to have highest influence on the assets, one would be investing in. There is no limit on the number of data that can be put into algorithm. Moreover, these can be completely different group of inputs for each of the assets. There are 4 assets analyzed as presented on plot 3.1. After input has been prepared, Principal Component Analysis (PCA) is applied to reduce the dimension of the data - only key information are extracted from the inputs. PCA outputs a set of series, which are applied as an input for the Neural Network. Here, Evolutionary Programming (EP) is applied for training process. Once the network is trained, it produces a prediction. By calculating mean and standard deviation of this prediction series, two moments are obtained. Repeating the process n-assets time, a set of expected returns and expected volatility is obtained. Therefore, Markowitz model can be applied to calculate Optimal Risky Portfolio and finally, resulting weights for assets allocation can be used as an indicator for investment.

One has to remember, that described procedure applies to only one moment in time (i.e. one day). Usually, one day is not enough, and the process should continue until terminated. This is easily achievable by iterative "moving window" applied to input data.

Following sections will describe in more detail how each of the modules work.

3.2 Dimension reduction

To achieve reasonable Neural Network training time, one should prepare no more than 10 input series, above which, time required for Neural Network to run is unacceptable. Therefore, using more than 150 different data series as an input, this had to be reduced down to 6 principal components which are produced by Principal Components Analysis. This linear method, based on calculation of eigenvalue decomposition of covariance matrix produces lower dimension "picture" of the whole set. Often high dimensional data set contain series which are highly correlated to each other. PCA is able to maximize variance between series and this maximum variance set is called principal components. Often, first few components contain most of the information contained in data, thus they are selected to be processed further. As presented on figure 3.2, first 5 principal components contain more than 90% of data. This is huge reduction and allows for extreme speed up of algorithm.

But one has to realize, that PCA is not a perfect algorithm - it is linear, thus often by applying it, often nonlinear information can be lost. But here, this problem has been considered to be a minor one, because of great advantages, as presented.

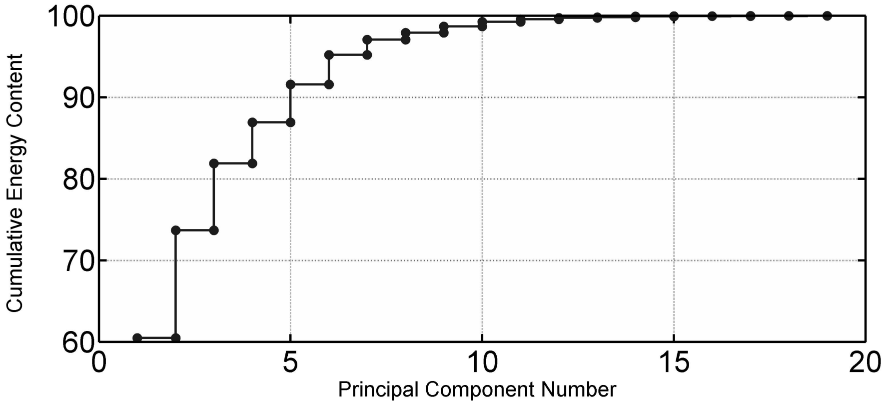
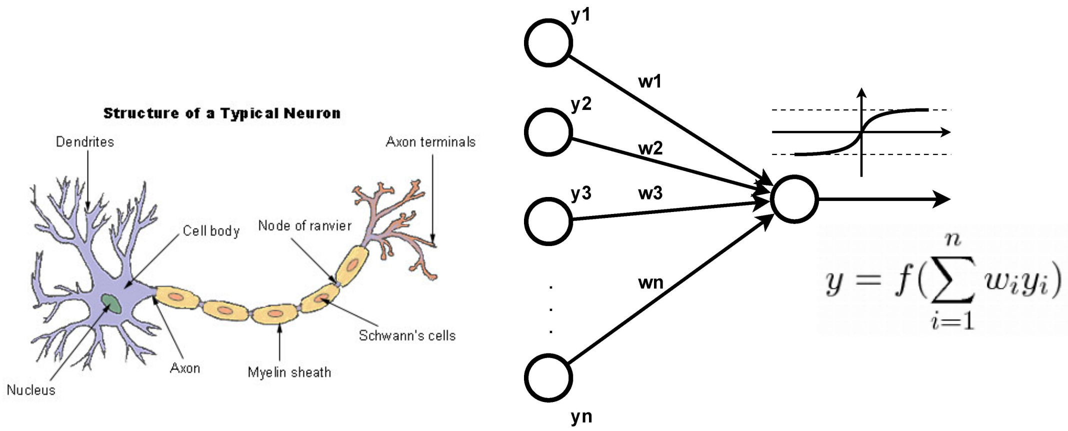


Figure 3.2: Energy content of principal components

3.3 Neural Networks

Neural Networks are the main building block of the algorithm. The history of this algorithm is very interesting but due to the limited scope of this work, it will not be described in detail. More details can be obtained from Krose & van der Smagt (1996), Hu & Hwang (2002), Haykin (2005) or Kamruzzaman et al. (2006).



(a) Biological Neuron (b) Mathematical Neuron

Figure 3.3: Neurons

The idea of Artificial Neural Networks (ANNs) has been based on the functioning of the human brain. At the beginning of research in this area, scientists believed, that by mapping structure of the brain and "translating" it into computer algorithm, they will be able to built thinking machine. What was the result? No intelligence has emerged, at least in the core meaning of the word, but powerful algorithm which can approximate virtually any nonlinear function. With number of limitations and simplifications, soon everyone realized that although it was possible to use it in many situations, never possible before, it could not help to build consciousness, which human posses and which allow them making decisions. Why? For number of reasons, but key factors were those simplifications which were applied to run algorithm, but which completely transformed it from the natural structure - even though general scheme has still been left similar. There was no doubt, that human brain was much more complicated than what has been developed as a mathematical description of it.

However, developed algorithm by scientists algorithm found applications in further research and finally even in the industry. But how does it work and which of its properties allowed for such expansion?

Human brain is constructed of billions of interconnected units called "neurons". Figure 3.3(a)[1] presents a biological neuron. Each unit is characterized by inputs - dendrites, processing core - nucleus - which is an analogy to CPU in desktop computer and output - axon. Inputs are designed to collect signal - electric impulses - from outside the neuron. Everything happens in sequence, not continuously. If at one moment in time, those electric impulses summed together will generate current strong enough - stronger than threshold - processing core will activate output impulse which through axons will be transferred to subsequent neuron connected with it. However, if the sum of inputs is not high enough to activate processing core, no output impulse will be generated.

Mathematicians "translated" above biological procedure into mathematics and as a result Artificial Neuron has been created as which is presented on figure 3.3(b). One can see many similarities in structure, but operation of calculating the output has been reduced to simple arithmetic addition and multiplication with nonlinear transformation as a final step.

All the transformations occur in the most important element of each neuron: nucleus. It uses nonlinear transformation of input to generate output, similar to sigmoid function. This feature introduces nonlinearity to the whole model and this property is one of the biggest advantages of neural networks. By combining enough neurons together, it is possible to approximate any nonlinear function as proved later by Hornik et al. (1989). There is a vast number of research available on this model, but unfortunately, it has still not been fully understood and is regarded as "black box" approach. Despite this fact, it has been successfully applied in finance world. Great survey about specific techniques has been provided by Dunis et al. (2003), McNeils (2005) or Kamruzzaman et al. (2006) to mention just a few.

For the purpose of this work, decision had to be made about specific kind of Neural Network. Here, algorithm has been chosen based on work performed by Radlak (2007). In short, whole structure has been represented as a directed graph with only forward connections available (figure 3.4). Each connection has been assigned an importance value (weight) and inserted into the matrix of the whole structure (i.e. 3.5). Value zero means that there is no connection between particular Neurons, value other than zero indicates how important the connection is (greater the value - higher importance of connection).

[1] Source: `http://www.web-books.com/eLibrary/Medicine/Physiology/Nervous/neuron.jpg`

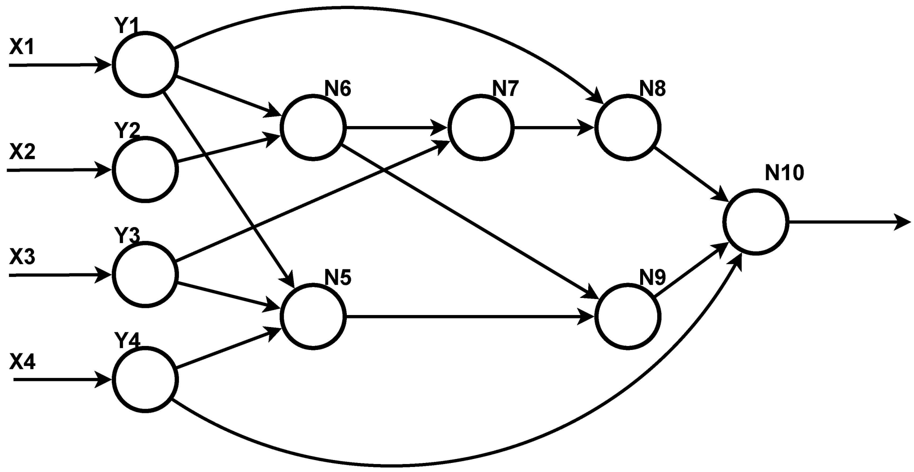


Figure 3.4: Example structure of Neural Network

y		1	2	3	4	5	6	7	8	9	10
y_1	1		0	0	0	.1	.2	0	.1	0	0
y_2	2	0		0	0	0	$-.2$	0	0	0	0
y_3	3	0	0		0	.7	0	5	0	0	0
y_4	4	0	0	0		.3	0	0	0	0	.1
y_5	5	0	0	0	0		0	0	0	.1	0
y_6	6	0	0	0	0	0		.7	0	$-.3$	0
y_7	7	0	0	0	0	0	0		.3	0	0
y_8	8	0	0	0	0	0	0	0		0	$-.4$
y_9	9	0	0	0	0	0	0	0	0		.3
y_{10}	9	0	0	0	0	0	0	0	0	0	

Figure 3.5: Example ANN representation in matrix notation

To calculate final output, following algorithm has to be applied:

1. calculate sum of products between connected neurons and their weights

$$\sum_{j=1}^{n} w_{ij}x_j \tag{3.1}$$

2. add bias

$$\sum_{j=1}^{n} w_{ij}x_j + 1w_{1b} \tag{3.2}$$

3. pass it through nonlinear transfer function.

$$y_1 = f_i(\sum_{j=1}^{n} w_{ij}x_j + 1w_{1b}) \tag{3.3}$$

4. output is equal to: y_1

The biggest problem with Neural Networks is assigning appropriate weights and the process of arriving to the best configuration of their values is called training. During this process, one provide an input set and expected output set. By modifying weights' values, one can find such configuration, that for a given input, produced output will be very close to desired. The measure of fitness could be i.e. Mean Square Error. One has to realize, that it is not obvious that larger training size will provide better performance - to large, in case of time series, can cause training on outdated set. Therefore, algorithm used to tackle the problem with training is Evolutionary Programming which is a global optimization method.

3.4 Evolutionary Programming

Evolutionary Programming (EP) is another algorithm which has been developed by scientists observing nature. It has been inspired by Darwinian theory of evolution. Darwin (1859) suggested, that species compete between each other and only the best can survive and produce offsprings. They evolve to adapt to continuously changing environment striving for survival. This type of behavior lead to constant improvements of species and better adaptation of individuals. And this idea has been applied in EP.

A population of solutions is at first generated randomly. In case of ANN, solution is a string of weights. These are then evaluated and ranked, depending on how good results they produce (i.e. which allow for output with lowest MSE). This is called fitness calculation. Then each member of population is modified (mutated). This is often achieved by multiplying randomly chosen value (or values) in the string by another random number. Process is repeated for each member of the population. Finally, fitness is compared between each other and only the best species are saved for next iteration. Whole process is illustrated on figure 3.6 and no more detailed description of this algorithm will be provided here due to the scope of this project. Further information can be found in following publications: Holland (1975), Michalewicz (1996), Mitchell (1996), Yao et al. (1999), Back et al. (2000*a*) and Back et al. (2000*b*).

3.5 Group of experts

Evolutionary Programming produces a population out of which one is the best, that means, result in the lowest training error. But often, very low MSE for training might result in very high MSE when evaluating Neural Network. This problem arises because of over-fitting problem and simply means, that excellent performance has been achieved for known data set, but if unknown data are introduced - algorithm is not able to perform well. Although it is impossible to obtain MSE equal to zero, the goal is to achieve relatively stable output for data that is know and which is not. One of known methods are out-of-sample tests.

This problem has also been considered in this work. The solution proposed was to use whole population of solutions, rather than just one. Intuitively, population generated

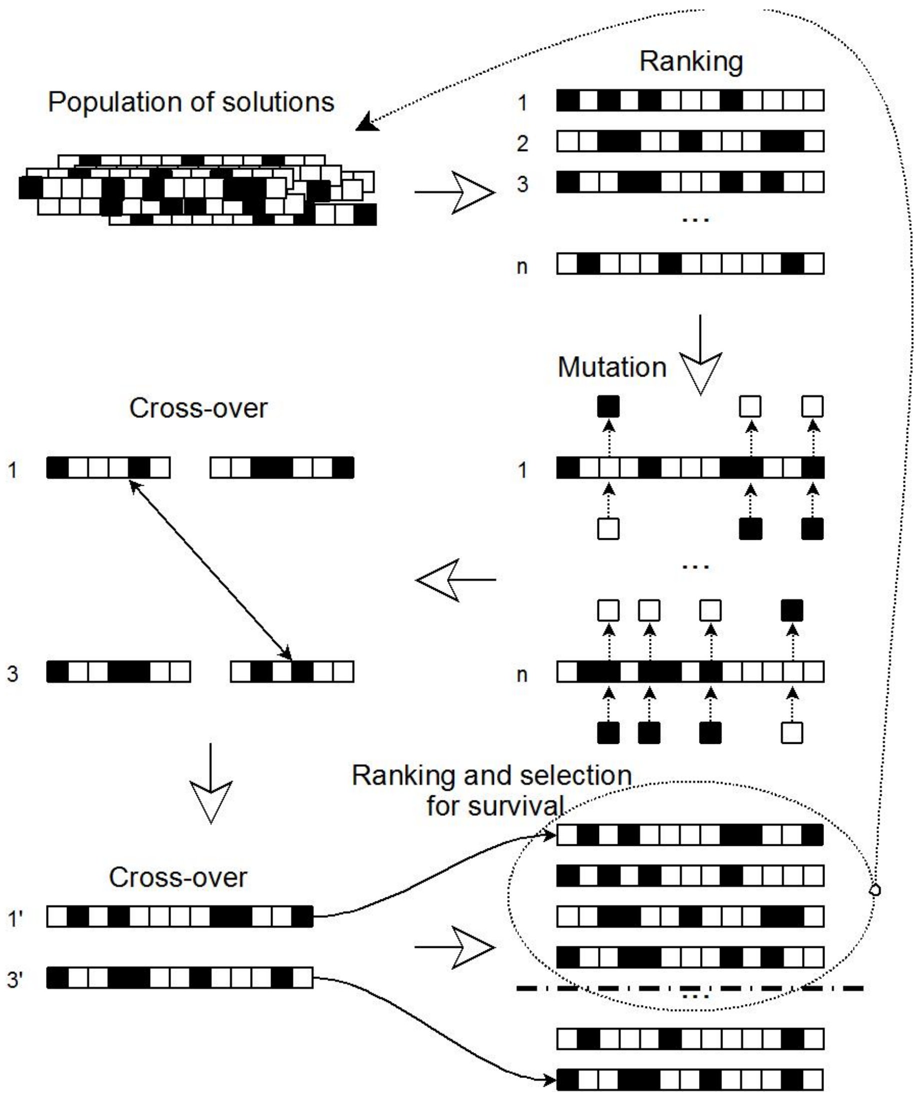


Figure 3.6: Evolutionary Programming Schema

by EP consists of those which are very good and those which are worse, but still were able to survive during many iterations of training process. This suggests that appropriate combination of all of them might result in better, more stable overall results.

This approach is called Ensemble of Experts. Each weights configuration is regarded as an Expert. For each of the Experts, output is produced for an evaluation input. In terms of time series predictions, few experts will predict growth, others will predict fall. By averaging those "opinions", by the law of averages, result is expected to be more accurate.

This is similar to the real world predictions of economic factors: experts are surveyed on their opinion about future value of key economic indicators. Their answers are further averaged and provided as a prediction before real value is announced.

In case of this project, produced outputs have been averaged using median. This is more reasonable method as some opinions might be completely unrelated to the others. Applying average to them would result in more biased opinion.

3.6 Markowitz Model

Markowitz (1952) in his work suggested an algorithm for portfolio optimization. This work was a foundation of Modern Portfolio Theory (MPT) which is a mathematical theorem, proving advantages of diversification. By including assets with different risk characteristics and correlation between them, it is possible to achieve higher returns, for the same amount of risk or even lower. This idea was an inspiration for currently conducted work.

Investors base their decisions on how big returns are possible. Unfortunately, higher the returns - higher the risk involved. Therefore, each individual decides how much risk he is willing to undertake. In terms of many assets, the convention is to characterize them in terms of those two values (in simples form): expected returns - expressed as an average returns over some period of time, and risk - expressed as standard deviation calculated over a period of time. Risk/Reward pair is usually different for every investment vehicle. But when combined together into a portfolio, one can reduce risk significantly and even increase returns due to mathematical properties showed by Markowitz. For a number of different assets, there exists only one set of allocation weights, which will produce highest Reward to Risk. This is called Optimal Risky Portfolio (figure 3.7) and is nothing else than pareto-optimal set of solution for multi objective optimization problem.

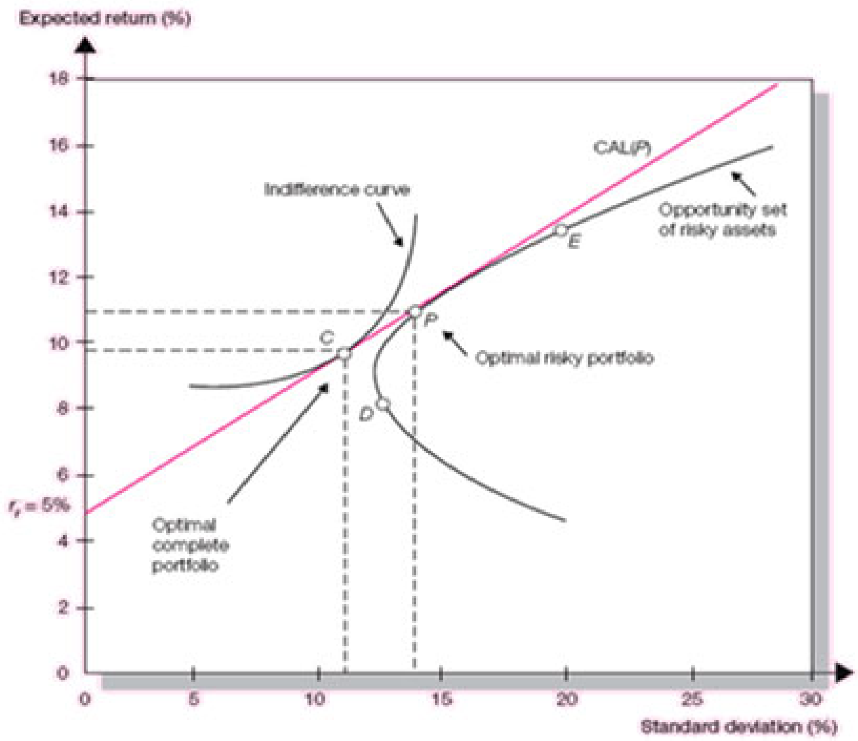


Figure 3.7: Optimal Risky Portfolio

MPT is the final element of the whole project. This module will transform predictions obtained from Ensemble of Experts, for each of the assets, into weights indicating how allocation should be done, to obtain Optimal Risky Portfolio when the investment will be performed.

3.7 Whole system combined

Figure 3.1 presented the structure of whole system and each element has been described in previous sections. However, to provide clear view of its functioning, following pseudo-code of required operations has been prepared:

1. Assign: i = 0, trainingSize = X, evaluationSize Y
2. For i = 0 to i smaller than dataSize
   (a) For j = 1 to j = numberOfAssets
      i. Prepare input and output:
         A. training: fetch data from i to trainingSize + i
         B. evaluation: fetch data from trainingSize + i to trainingSize + evaluationSize + i
         C. reduce dimension using PCA
      ii. if (i = 0) then train ANN from beginning;
      else retrain ANN based on structure obtained in previous iteration.
      iii. evaluate ANN
      iv. obtain population of outputs
      v. combine outputs
      vi. calculate Risk and Expected Return for predicted data
   (b) Calculate Optimal Risky Portfolio
3. Increase i = i + 1.
   If (i larger than dataSize) then stop. Else go back to 2.

There are no limits to the length of algorithm functioning. It has been designed for infinite use. Therefore, if new data become available, algorithm can be re-run using just new data (Assuming that data from previous iterations have been saved).

3.8 Additional solutions for encountered problems

Finally, to support presented algorithms of high complexity, there were number of small issues encountered which had to be solved during the course of this project. These will be presented as follows.

Problem of data re-scaling

In this project, neurons with logistic transfer function have been used. This cause problem, that output can only be in a range $[-1, 1]$. Therefore, a simple method for obtaining real value output has been used. As a requirement, there were two sets prepared: training and evaluation. In case of training set, for a training input, desired output has been known. But, because of the problem discussed here, it was not possible to use raw value of assets as an output, thus it has been re-scaled, to be in a range $[-1, 1]$ using equation 3.4.

$$y_t = 2\frac{x_t - min}{max - min} - 1 \;\Rightarrow\; y \in [-1; 1] \tag{3.4}$$

To be able to compare Neural Network's output with real asset value it was possible to scale it back using equation 3.5, which is just a mathematical transformation of eqn 3.4.

$$y_t = 0.5(y_t + 1)(max - min) + min \tag{3.5}$$

Therefore, if a prediction has been calculated in a range $[-1, 1]$ using evaluation set, it was possible to obtain real value of assets. Max and min values used were those, which were calculated from training set. There was a risk of data loss, if the prediction would be larger than maximum value for the data, but after tests, it was evident, that this situation happened very rarely.

Combining historical data with Neural Network predictions

Predictions from Neural Networks are expected future values of assets. On the other side, simple mean and standard deviation for MPT are calculated based on historical data. Both have advantages, i.e. predictions inform investor about expected future behavior. Calculations based on history involve assumption, that what happened in the past, is most likely to happen in the future.

However, predictions are not always accurate and historical data often outdated. Therefore, an idea emerged to combine both of the data. Therefore, tests in chapter 5 will involve performance evaluation of portfolio produced from combination of Neural Network predictions and historical data. This is presented on figure 3.8

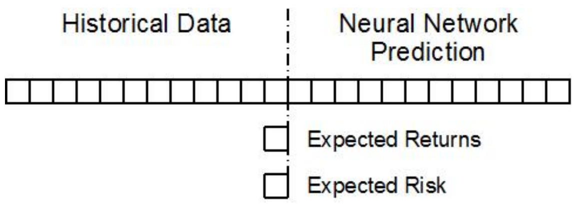


Figure 3.8: Combined historical and predicted data

Chapter 4

Data description and analysis

Previous chapter presented the algorithm which will be used to process the data. Here, description of applied data set will be performed, because it is very important element of the project. Each time series has been downloaded from *Thomson Datastream* (2008). As mentioned in chapter 3, two groups had to be prepared: input set and desired output set. These will be described in detail in the following sections. Researched period has been set to be 7 years back from present, that is from 18 th of July 2001 - 18 July 2008.

4.1 Output

This is major decision, because based on what will be selected, final portfolio will consists of. Therefore, one would prefer liquid and popular assets, easily available. They should be easily traded long and short. Therefore ideal investment seemed to be futures contracts on stock market indices. These certainly meet all the above requirements. Thus finally, as an output, 7 major stock market indices futures have been selected:

- German - DAX futures,
- French - CAC 40 futures,
- Japanese - NIKKEI 225 futures,
- Polish - WIG 20 futures,
- British - FTSE 100 futures,
- US - NASDAQ 100 futures,
- US - S&P 500 futures.

Due to contract expirations, only last 3 months have been selected for analysis as during this period, liquidity is always highest. As soon as contract was due to expiry, contract series has been changed to the one which would expiry next. Fortunately, *Thomson Datastream* (2008) provided a time series which has already been transformed in a described way, thus continuous series has been obtained for each of the contracts. This way, splicing has been avoided.

Table 4.1: Descriptive Statistics for output futures returns

	Dax	Cac 40	Nikkei 225	Wig20	Ftse 100	Nasdaq 100	S&P 500
Mean (*Annlzd*[%])	0.53	1.13	-0.11	10.04	1.07	-1.73	1.48
Std Dev (*Annlzd*[%])	16.46	25.08	17.88	24.55	21.47	22.03	24.39
Sharpe Ratio	-0.27	-0.15	-0.27	0.21	-0.18	-0.15	-0.14
Median	0.000346	0.000092	0.000000	0.000000	0.000000	0.000282	0.000219
Mean	0.000059	-0.000069	0.000043	0.000401	-0.000004	0.000045	0.000021
Std. Dev.	0.015427	0.013931	0.013580	0.015524	0.011306	0.015861	0.010409
Skewness	-0.488847	-0.137131	-0.311057	0.135902	-0.181361	0.048253	0.011832
Kurtosis	10.33846	7.010811	4.347193	4.796130	6.865679	6.464078	6.013734
Jarque-Bera	4172.330	1230.319	167.6237	251.2094	1147.588	914.1964	691.4552
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.072889	0.071011	0.045175	0.075885	0.059506	0.102675	0.057549
Minimum	-0.148167	-0.083061	-0.061987	-0.063286	-0.060625	-0.092420	-0.054385
Observations	1827	1827	1827	1827	1827	1827	1827

4.1.1 Descriptive Statistics, normality and correlation

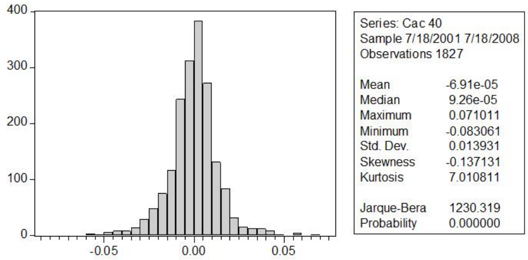
Following table 4.1 presents descriptive statistics for the output returns. There are two types of mean and standard deviations calculated: annualized (expressed in terms of percentages) and non-annualized (expressed in decimal points). Additionally, figure 4.1 has been prepared to visualize distribution of analyzed returns. Presented data have been calculated based on daily values.

It can be seen that none of the assets is normally distributed according Jarque-Bera test. This might be because of sample size being not big enough. However, as one can see, departure from normality is not very large, thus to fulfill Markowitz assumptions - it has been assumed that the returns are normally distributed. Additionally, if the size of data would be extended, it is very probable, that characteristic would diverge less from required values for normal distribution.

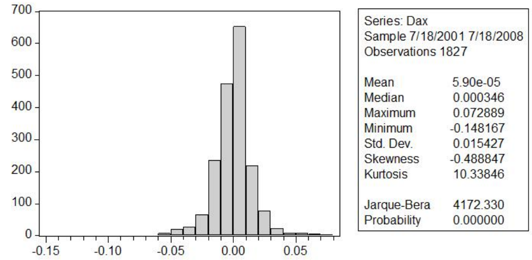
Finally, cross-correlation has been calculated and presented in table 4.2. Although correlation between the assets is low, there is no asset with negative correlation as this would allow for significant risk reduction. As one can notice, some assets are almost un-correlated between each other. This is very important property, which will increase benefits of diversification.

4.1.2 Performance evaluation

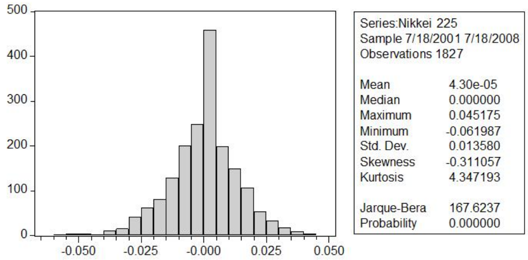
Above results provide only overview of the data that has been used in this project. It is not possible to use it as a benchmark, because structure of final output will be completely different - it will be a portfolio. Therefore, performance will be measured in few different ways. First, as a benchmark, buy and hold strategy for the portfolio will be considered and



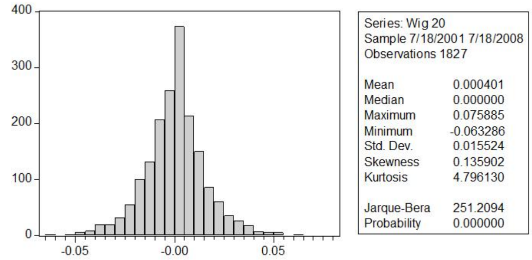
(a) French Cac 40



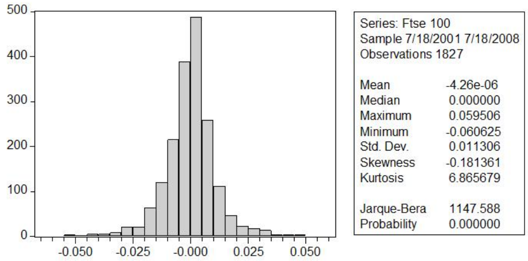
(b) German Dax



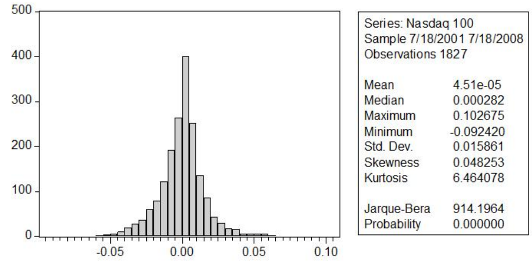
(c) Japanese Nikkei 225



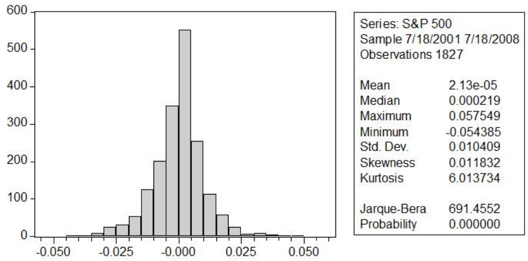
(d) Polish Wig 20



(e) British Ftse 100



(f) US Nasdaq 100



(g) US S&P 500

Figure 4.1: Histogram and individual statistics for output futures series

Table 4.2: Cross-correlation for output futures returns

	Dax	Cac 40	Nikkei 225	Wig 20	Ftse 100	Nasdaq 100	S&P 500
Dax	1.00	0.83	0.19	0.40	0.75	0.50	0.56
Cac 40	0.83	1.00	0.26	0.44	0.88	0.40	0.48
Nikkei 225	0.19	0.26	1.00	0.20	0.24	0.15	0.13
Wig 20	0.40	0.44	0.20	1.00	0.43	0.23	0.25
Ftse 100	0.75	0.88	0.24	0.43	1.00	0.34	0.44
Nasdaq 100	0.50	0.40	0.15	0.23	0.34	1.00	0.86
S&P 500	0.56	0.48	0.13	0.25	0.44	0.86	1.00

to enable comparison - Sharpe (Sharpe (1964)) Ratio[1] will be used. Secondly, strategy, based on simple mean and standard deviation, mimicking proposed algorithm will be used as a benchmark. This way, it will be possible to test if the algorithm is able to beat simple historical approach. Another tests that will be performed would be to examine only predictions from the algorithm as a base for calculating asset allocation. Finally, combined historical and predicted data will be used to calculate optimal weights for assets allocation.

4.2 Input

Deciding about output series follows decision about an input. This is complicated issue, because one has to have an idea of what can influence chosen output series. Assumption of the work has been to automate process of decision about assets allocation in portfolio. Trying to imitate human expert, who analyzes vast number of different data, the strategy of collecting any valuable input has been adopted. This approach resulted in approximately 150 daily time series for each of the index futures analyzed.

According to Efficient Market Hypothesis Fama (1965), share price (futures prices in this case) reflects all the available information. Stock Market Index futures are definitely influenced by economic indicators, prices of commodities, interest rates, exchange rates, etc. Lahiri & Moore (1991) states that there are 11 leading economic indicators, which can provide excellent overview over economic situation. These are the first presented on the following list.

- New orders, consumer goods and materials
- Contracts and orders, plant and equipment
- New housing permits
- Average weekly hours of production workers
- Percentage of companies receiving slower deliveries
- Stock Price Index
- Change in Sensitive material prices
- Money Supply (M2)

[1]Risk Free rate will be assumed to be 5%

- Initial Claims for Unemployment Insurance
- Change in Business and Consumer Credit
- Change in Manufacturing Inventories

This list has been expanded to include as many indicators as there were available on the *Thomson Datastream* (2008). Following list provides an overview of just a few series included out of approx 150 for each of the futures contract (full list is available in Appendix):

- Bankruptcy Fillings
- Chicago Purchasing Manager Barometer
- Consumer Confidence Index (CCI)
- CPI - All items less food & Energy
- CPI - All items
- Current Account Balance
- Federal Funds Rate
- Foreign Reserve Assets
- GDP
- GNP
- New Orders - All Manufacturing Industries
- New Private Housing Units Started
- PPI - Finished Goods
- PPI (Core) - Finished Goods Less Foods & Energy
- Unemployment Rate
- Unemployment Rate - Initial Claims
- University of Michigan Consumer Sentiment Index
- US 3 Months Interbank Rate (London)
- Visible Trade Balance
- Brent Crude Oil Settlement Price
- 100oz Gold Settlement Price
- PLN/EUR - Exchange Rate
- PLN/JPY
- PLN/GBP
- PLN/USD
- EUR/GBP
- USD/JPY
- USD/GBP
- DAX 30 - Price Index
- CAC 40 - Price Index
- Dow Jones Industrials - Price Index
- FTSE 100 - Price Index
- Hang Seng - Price Index
- NIKKEI 225 - Price Index
- NASDAQ 100 - Price Index
- WIG 20 - Price Index
- S&P 500 - Price Index

Algorithm presented in chapter 3 has been designed in such a way, that virtually any data, but with similar structure to those used in this project, can be processed. There are no artificial limitations for the number of input series. Algorithm will detect different countries located in separate spreadsheets and also will detect number of inputs located in columns. Obviously some of the data will be redundant, but this is the task of PCA to produce series of few principal components which will contain most of the information available in the data. After number of trials, it has been decided, that five most significant components will be used by default. This is a tradeoff between the efficiency and accuracy of algorithm. Higher number usually lead to better performance of Neural Network (obviously too high will result in over-fitting to data), but the speed of execution reduces unacceptably. Low value on the other side results in speed increase, but reduce accuracy.

4.3 Algorithm settings

As it was already mentioned, Artificial Neural Networks have huge number parameters, which can be modified. Coupled with Evolutionary Programming algorithm - possibilities of fine tuning become unlimited. Therefore, it was a must to decide about appropriate default values for many variables. Following list will provide setting for those most important ones. These has been set based on experience:

- Evolutionary Programming
  - Gradient: 0.000001
  - Termination fitness for training epoch (MSE): 0.02
  - Maximum number of evaluation iterations for one epoch: 5000
  - Population size: 100
  - Maximum value in solution string: 1
  - Minimum value in solution string: -1
  - Maximum variance in EP algorithm: 0.1
- Neural Network
  - Number of input Neurons: 6
  - Number of hidden Neurons: 5
  - Overall number of Neurons: 11
  - Solution string length: 45

With above parameters, predictions were performed for Index Futures. Having this, it was possible to calculate returns and then in a predicted sample. Then, mean returns and standard deviation have been calculated and which further have been used in estimating efficient portfolio.

There was a problem of choosing the right prediction size and as it is important parameter, process of finding the best value would be described in the next chapter. This parameter, together with with training set size, were altered to obtain best performing portfolio. Just as a guideline, prediction set size ranged from as low as 25 up to 200 days ahead. Training set size ranged from as low as 125 to 500 days from the past.

Chapter 5

Results, analysis and discussion

This part is designed for presenting all the results obtained from algorithm presented in chapter 3.

5.1 Optimal Portfolio benchmark

As one of the results obtained from used algorithm was an optimal portfolio for each of the day in analyzed time frame. Based on framework described in **??**, number of options have been tested, to obtain best possible results. Therefore, strategies for this part of the project have been divided into three groups:

- estimation is based purely on historical average returns and standard deviation
- estimation is based purely on prediction of neural networks
- estimation contains two series: first half is the most recent historical data, second half - most present neural network prediction - this way, size of an estimation sample will be maintained

Following sections will describe the results that were obtained. It is important to remember, that due to long time required to run algorithm, obtained results are not as full as one would like to see, but are certainly enough to come up with conclusions.

5.2 Simple Mean and Standard Deviation

In its standard form, Markowitz approach is static - does not include changes that occur within financial markets. Expected returns and volatility are calculated on the basis of some fixed period of time. But in real world, once an initial investment has been made, one has to continuously monitor the portfolio. It is obvious that weights calculated today for optimal risky portfolio, may change dramatically tomorrow, because of i.e. some unexpected event.

As a result, following tests have been performed in order to understand how does the model perform over the period of time, when weights are updated every single day - so assets allocation is always optimal.

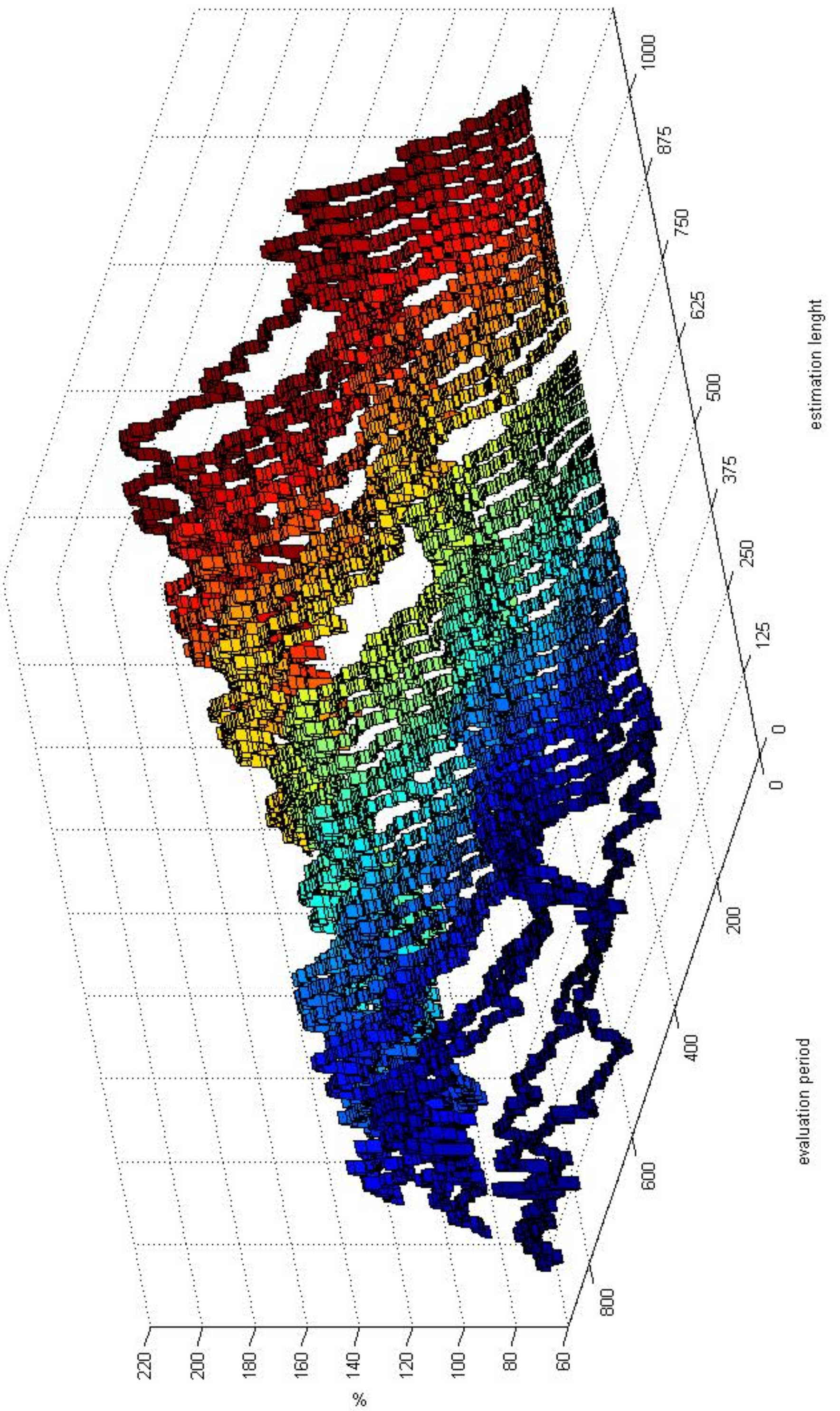


Figure 5.1: Portfolio value based on estimation period length

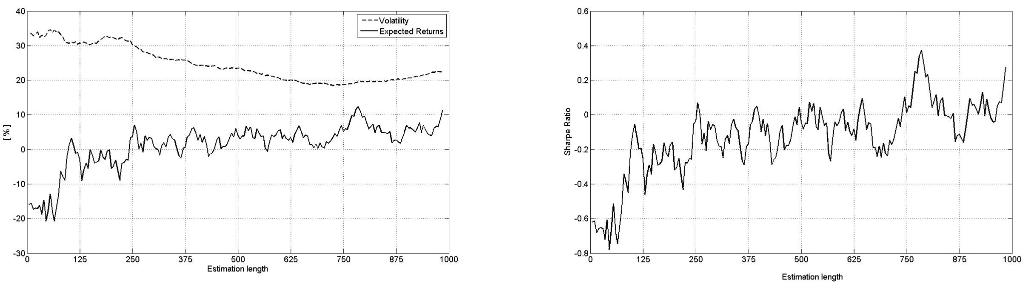
Forward Moving Optimal Risky Portfolio

Here, influence of length of estimation period for expected returns and volatility has been tested. Based on full 7 years of available output data, estimation period has been altered between 25 days - 1000 days and value of portfolio has been calculated. Weights and Portfolio value have been updated every day in evaluation period containing 828 days (whole sample size minus maximum estimation size). To increase comparability - performance of each portfolio has been re-based to 100 at the beginning of 828 days. Figure 5.1 presents general overview of the resulting experiment.

Analyzing this phenomena further, expected returns and risk of resulting portfolio value has been calculated and visualized in the figure 5.2(a).

One can observe very interesting feature in the results. For very low estimation period, volatility of the portfolio is high - expected returns very low. As seen on figure 5.1, performance for estimation period lower than approx. 100 days is very low - even less than zero. Low estimation period introduces high volatility into the portfolio together with dramatic reduction in expected returns. Obtained values, are worse than each of the assets separately (compare with Table 4.1) what is proven by calculating Sharpe ratio. Unfortunately, plot for expected returns on figure 5.2(a) is very volatile thus one has to be cautious while making conclusions about specific "best" estimation range. However, excluding to low estimation periods, expected returns oscillate between 5 and 10%.

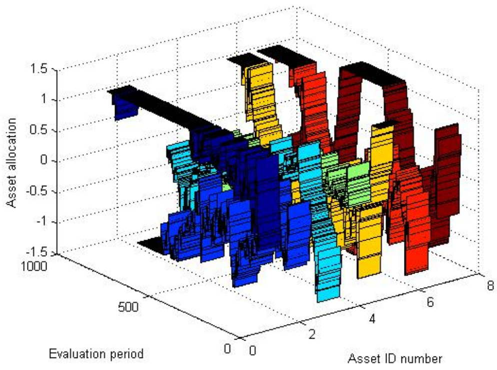
By looking at volatility of daily re-balanced portfolio on figure 5.2(a), one can notice that it is very stable, achieving minimum at around 650 - 700 days. Figure 5.2(b) presents value of Sharpe Ratio[1]. Although its plot is also volatile, one can extract a growing trend until 750 days and decreasing afterwards.



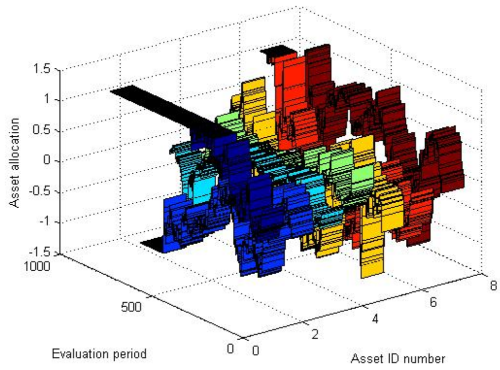
(a) Expected Returns and Volatility (b) Sharpe Ratio

Figure 5.2: Values for Optimal Risky Portfolio re-balanced daily during evaluation period

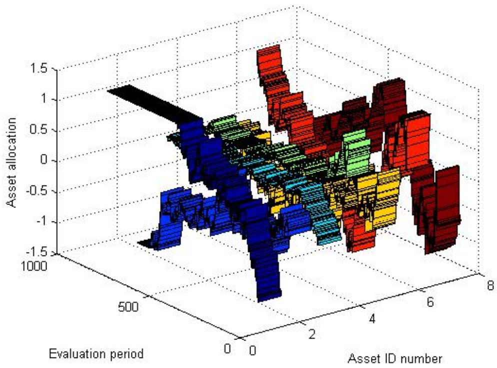
[1]Note: Risk Free Rate used to calculate Sharpe Ratio has been set to 5%



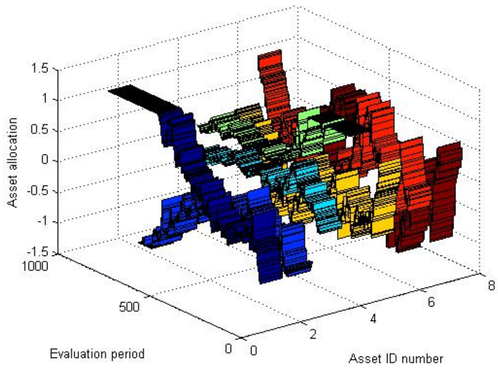
(a) 250



(b) 500



(c) 750



(d) 1000

Figure 5.3: Assets weights updated for each consecutive day with respect to estimation period length

Key notes

The results are not very impressive because transaction costs have not been included in calculations. Figure 5.3 provides an overview over re-balancing which has to occur every day to maintain optimal risky portfolio. Maximum and minimum asset allocation has been set to 1.3 and -1.3 for long and short position respectively. Figure 5.4 has been prepared provide an overview for how allocation is performed. The method of preparation is simple, however allows to understand which assets are favored. Additionally, if one has to re-balance a portfolio, the amount that has to bought/sold has significant influence on the cost of transaction.

On average, the amount of particular asset hold in portfolio is presented in first column. As one can see, depending on estimation period, algorithm may favor other assets, i.e.: Asset $A4$ overweighed for shorter estimation period while asset $A5$ is almost excluded from portfolio but its exposure is increased while longer estimation period is assumed.

There is also one more feature visible on figure 5.4 - average asset allocation is characterized by relatively low sensitivity with regard to estimation length. This is confirmed on sub-figure 5.4b, that by increasing estimation period - re-balancing becomes smoother.

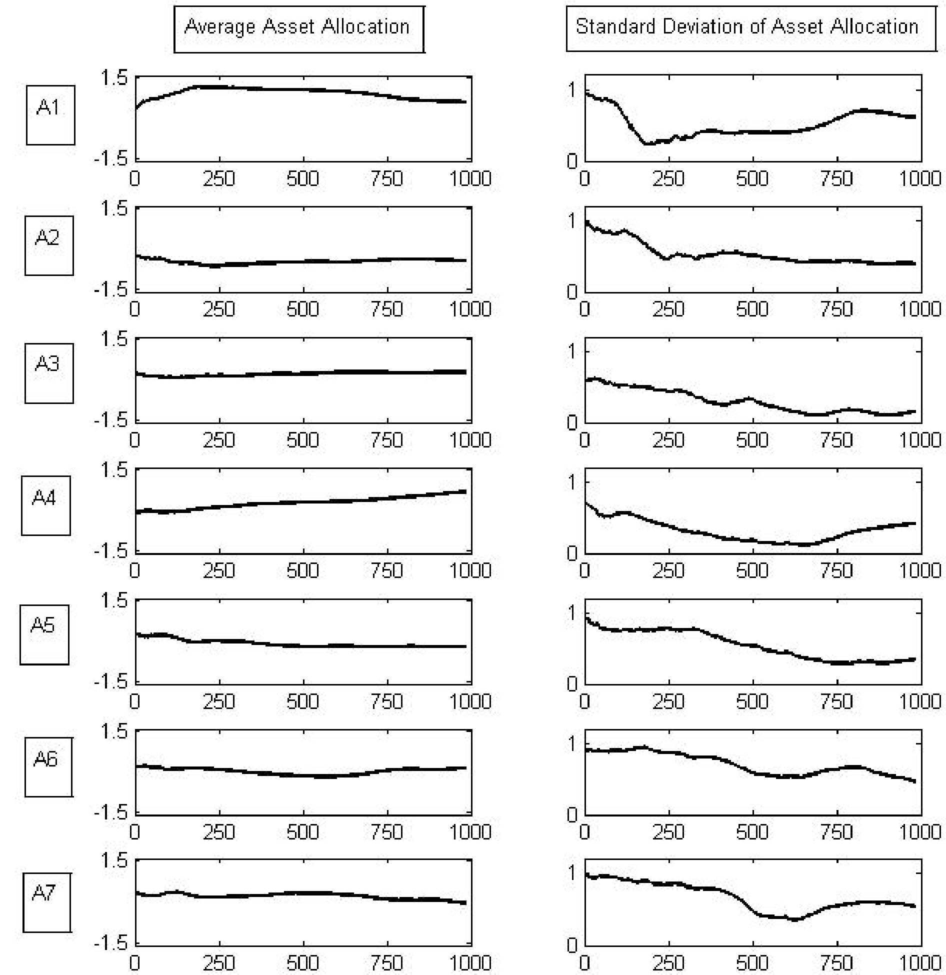


Figure 5.4: Asset allocation and its standard deviation presented for each asset separately

Standard deviation of asset allocation - measure of how big re-balancing has to be performed - reduces with the increase of estimation length. But this is observed until some "saturation" level, since which volatility of asset allocation rises, i.e. for analyzed period and assets, value around 600 - 700 days.

5.3 Introducing Neural Networks

When applying Neural Networks, one would requirer that they will produce predictions. It is important to emphasize, that there are dozens of parameters that can be used to fine tune algorithm. Here, few pre-tests have been performed and based on experience, those which produced the best initial results, have been adopted for the whole analysis.

Therefore analyzing Neural Networks output is much more complicated and requires much detailed approach than in case of simple mean and standard deviation.

Neural Networks produce an output which is a prediction for the future. One has to decide, how long is the training period supposed to be, how long should the prediction be. It is obvious, that more we look into the future, the less reliable this prediction becomes. But on the other side, if the prediction is too short, then, we will not gain any advantage from applying Neural Networks algorithm. Finally, one has to decide, how to process the prediction, to be able to apply Markowitz optimization and produce Optimal Risky Portfolio. These problems have been approached in the following subsection.

Optimal Portfolio performance as a function of training and evaluation size

Markowitz algorithm requires a pair of Expected Returns and Volatility. To meet this requirement, using simple approach, one has to calculate mean and standard deviation of returns during a historical period of time. This has been done in section 5.2.

Neural Networks generate probable future values of assets. Therefore, instead of using historical numbers, it is possible to use future values to calculate expected average returns and expected volatility. And this approach has been adopted here. But, as mentioned before, one has to examine how long should the training and prediction be. Figure 5.5 presents Average Returns and Volatility for predictions made by Neural Networks. These has been plotted with respect to training size (how many days have been used to train the algorithm) and prediction size (how many days ahead the forecast has been done). Unfortunately, as presented, not many different parameters have been examined. This is because one test took more than 8 hours to run, thus to produce only those plotted data required approx. 100 hours of continuous calculations.

Analysis

By looking at figure 5.5 one can notice a pattern - there are some areas where average returns of predictions is high and this is accompanied by high Sharpe Ratio as seen on figure 5.6. This happens for prediction size equal to 100 days (in case of 500 days training size) or 75 days (in case of 250 days of training) and finally 25 (in case of 125 days of training - but here, there is no evident top as in case of two other examples). Based on above, one could conclude that the ratio of prediction to training should be definitely less than 0.5, being ideally between 0.3 and 0.2. This set up was able to produce high average returns for evaluation portfolio.

Although expected returns are higher than in case of simple approach, volatility is much higher, ranging between 17 and 28% (compared with figure 5.2(a)).

However, comparing Sharpe Ratio of those two approaches, obtained value are similar, but Neural Networks were able to increase it by 0.1%. This is not an impressive result, but if we were to analyze how much data has been used, Neural Networks are in an advantage: as few as 325 days have been required (250 training size plus 75 days of prediction size) - what is half of the data required in case of simple approach.

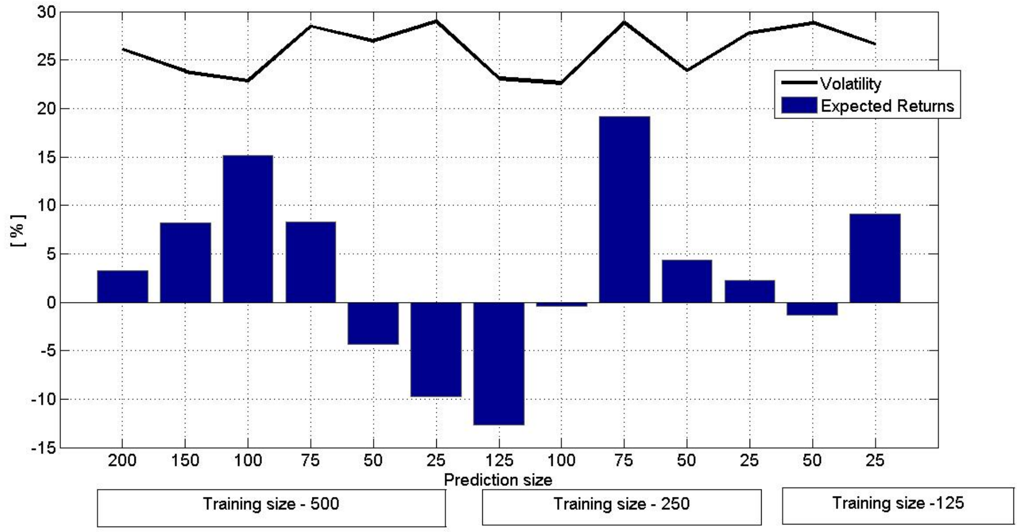


Figure 5.5: Evaluation Portfolio Expected Returns and Volatility based on training and prediction size

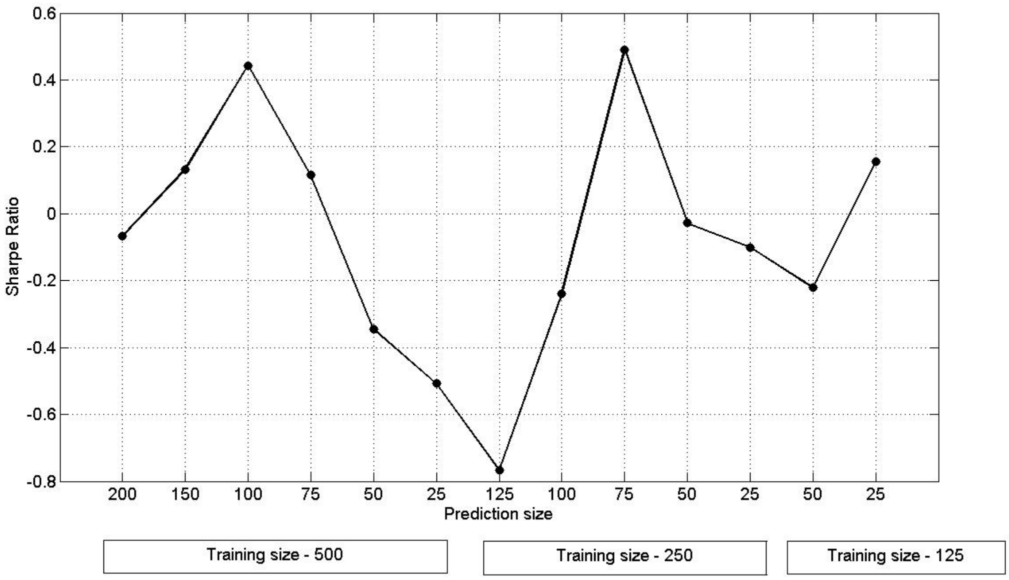


Figure 5.6: Sharpe Ratio based on training and prediction size

5.4 Combination of Simple approach and Neural Networks

As results presented in previous sections show, both algorithms provide similar results, with slight advantage on the Neural Networks side because of smaller estimation interval.

Therefore, an idea emerged to combine data from both of these algorithms. As a result,

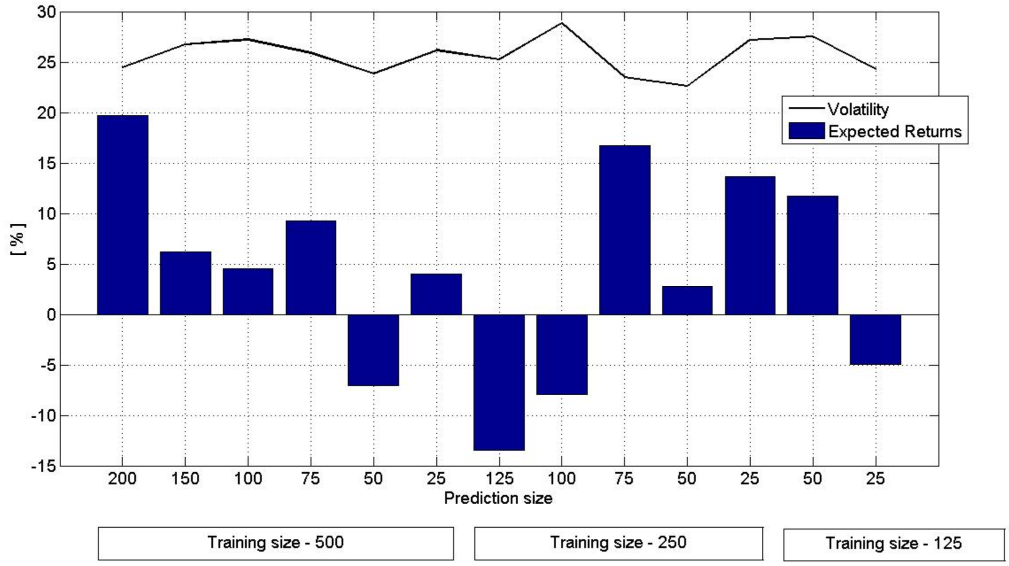


Figure 5.7: Evaluation Portfolio Expected Returns and Volatility based on training and prediction size (Simple Mean and Risk combined with Neural Network Output)

estimation of expected returns and volatility required to be plugged in to Markowitz algorithm will consist of historical (calculated using historical simple mean and simple standard deviation) and future data (predictions from Neural Networks). This is expected to solve problems for both of the approaches: inability to foresee future by historical method and inability of seeing how the asset performed in the past so one would know if predictions are consistent.

Analysis

When analyzing figure 5.7 one can notice that when training size equal 500 days, 200 days for a prediction set seems to be producing very good results, better than any of the configuration previously examined. Sharpe Raio (figure 5.8) equal to 0.6 is the highest achieved so far. Another peak at Sharpe Ratio figure occur for training size equal to 250 and prediction size of 75 days ahead (including 75 days of historical data). For this set-up volatility of portfolio is lower than for any other data set.

This confirms hypothesis that prediction set size should be more than 50% less than training size. Here, the ratio of prediction to training is between 0.3 - 0.4. It is slightly higher than in previous experiment, allowing for longer predictions by not extending training size. Therefore an effect of combining historical data with predictions seems to be in effect. Not only Reward to Variability ratio is improved, but also reduction in data required will occur.

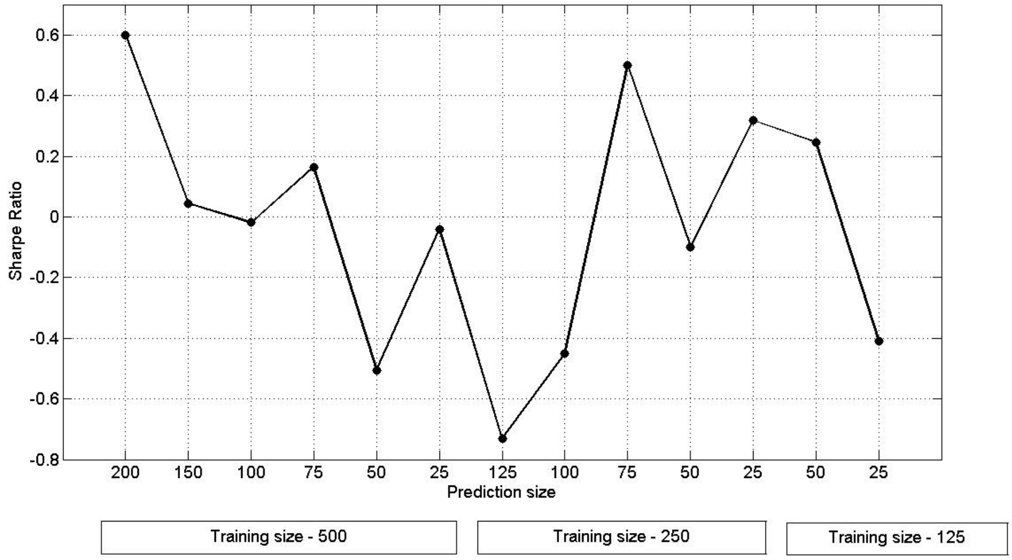


Figure 5.8: Sharpe Ratio based on training and prediction size (Simple Mean and Risk combined with Neural Network Output)

5.5 Investigating statistical significance

Table 5.1 has been prepared to gather all the important results for ease of analysis. Column named combined presents results of evaluation portfolio when predictions and historical data has been used. As clearly seen, each of the values are significantly different than zero. When only Neural Network predictions have been used as an input for Portfolio Optimization algorithm, there are few results, which are not significantly different than zero. This does not occur for large training size, but lowering it, introduced some insignificant results. Last column called difference of mean, presents the results which compare one approach to another. Using t-test, as in previous examples, significance of mean differences have been tested. As a result, there exist strong significance of results for longest training and prediction size (200 days). This is means that applying combined version improved performance. Looking at 100 prediction days unfortunately, combined version produced worse results. Analyzing 250 days training size, significant differences have been achieved while prediction size was 25 or 100 days. For the other ones, there was no significant improvement or decrease in performance. Finally, when training was 125 days, performance in case of 50 prediction days increased significantly, but when 25 days have been used, this reduced badly.

To summarize, combined approach greatly improved the best achievable return, with only slight increase in variability of portfolio - Sharpe Ratio increased from 0.44 to 0.60.

Table 5.1: Summary of results

		Combined				Neural Network only				Difference of means	
Training size	Prediction size	Mean Returns	Volatility	t-statistic	p-value	Mean Returns	Volatility	T-statistic	p-value	t-statistic	p-value
[$days$]		[%]		$H_0 : \mu = 0$		[%]		$H_0 : \mu = 0$		$H_0 : \mu_1 = \mu_2$	
500	200	19.7	24.4	23.141	0.000	3.3	26.1	3.63	0.000	13.18	0.000
	150	6.2	26.7	6.643	0.000	8.2	23.8	9.87	0.000	-1.60	0.110
	100	4.5	27.2	4.735	0.000	15.1	22.9	18.99	0.000	-8.59	0.000
	75	9.2	25.9	10.280	0.000	8.3	28.5	8.39	0.000	0.71	0.477
	50	-7.0	23.9	-8.500	0.000	-4.3	27.0	-4.61	0.000	-2.18	0.029
	25	4.0	26.2	4.351	0.000	-9.7	29.0	-9.65	0.000	10.08	0.000
250	125	-13.4	25.2	-15.311	0.000	-12.7	23.1	-15.83	0.000	-0.62	0.535
	100	-8.0	28.8	-7.940	0.000	-0.4	22.6	-0.50	0.618	-5.94	0.000
	75	16.8	23.5	20.503	0.000	19.2	28.9	19.11	0.000	-1.87	0.062
	50	2.8	22.6	3.535	0.000	4.3	23.9	5.21	0.000	-1.35	0.176
	25	13.6	27.2	14.459	0.000	2.2	27.8	2.28	0.023	8.47	0.000
125	50	11.8	27.5	12.296	0.000	-1.4	28.8	-1.37	0.172	9.47	0.000
	25	-4.9	24.3	-5.836	0.000	9.1	26.6	9.85	0.000	-11.21	0.000

Chapter 6

Summary, Conclusions and indications for future work

6.1 Summary

The main goal of the project was to produce and analyze algorithm which will at any time provide an answer to the following questions:

- *What is the best allocation of assets at the moment subject to changes in market conditions? (Word "best" is meant to be the highest return and lowest risk)*
- *How to re-balance the portfolio so it is always optimal.*

Have the goals been accomplished? With no doubt - yes. Developed algorithm is almost fully automated in such a way, that for a given input - it produces an output which is a set of weights for assets allocation, that will allow to achieve Optimal Risky Portfolio. This can be run iteratively, including new data every time it becomes available. This way, investor will always know, how much to invest in each particular asset in the portfolio at a specific moment in time.

The project was complicated in terms of programming. It involved approximately 500 lines of code written mostly in Matlab (with some parts programmed in C to increase speed). When analyzing size of data, if each data point would be summed together, the set would count more than 2 million points (7 year series times 7 assets times approx. 150 input variables). This resulted in long delays in calculating the output. To obtain results for specific settings, it required 6-8 hours of continuous calculations. And there were 13 different settings configurations tested.

Therefore, as seen in above statistic, project was time consuming and required good time management in order to analyze produced results and describe the whole process. Everything went smooth and mostly according to the plan prepared at the beginning. For the project of this scope it may also be regarded as a great success. Also because large data set has been analyzed, there are many information that the project provided. What conclusion can be drawn from these information this will be described in next section.

6.2 Conclusions

One important conclusion from the results presented in chapter 5 is that developed algorithm improved performance as tested during evaluation period which was long enough (828 days) to test it in stable, low volatile market as well as very highly volatile period started in August 2007. As results show, applying only predictions from algorithm, improved Sharpe Ratio by just 0.1, but combining historical data and predictions, allowed for increase of 0.2. This is not very impressive reward, especially, when considering the time required to obtain the results. But there was significant gain in the training size, which was reduced by half in case of predictions from Neural Networks. This is significant advantage. But these results also proved, how difficult it is to develop an algorithm, which would be predicting the future accurately. If results would allow for excessive returns, greatly exceeding those which can be obtained from standard methods - this would prove market inefficiency. However, it has not yet been proven with 100% certainty, that markets are efficient, there are overwhelming evidences, that this is the case indeed. Therefore there would be a great surprise if one would develop consistently profitable algorithm.

Despite the fact, that algorithm was not able to significantly beat the market, obtained results are very important - they confirmed, that diversification plays important role in assets management. Although volatility slightly increased for the whole portfolio, profits were much grater than in case of any single asset. Additionally, Sharpe Ratio was larger than for each of the assets (in case of best parameters setting obtained).

Another important issue that should be discussed are transaction costs. Daily rebalancing would generate some cost, which has not been included in calculations here. This was not necessary while comparing performance, because it was assumed that the cost for each day, for each asset in the portfolio using different method would be the same. Therefore, costs would not influence the results of comparison.

Next section would provide some ideas which could be used to tackle many problems.

6.3 Suggested improvements for the future work

As mentioned in previous section, costs were not considered in this project due to the limited scope. However, it would be an interesting research which would examine, how does the transaction cost really influence overall performance of portfolio. This is very important issue in fund management which cause never ending debate about what is better: active or passive investing.

Another problem that had an influence on the project was the speed of execution. If this would have to be a commercial algorithm, used in real life investing, it would definitely require speed improvements, because analysts would not be interested in waiting such a long time for the data to come. This would be accepted if the results were outstanding. And this issue could also be addressed - after speeding the algorithm up, it would be easier to test different parameters configurations and eventually one could find the setting which would provide impressive results. Finding best settings is very time consuming process now.

During the tests performed, an idea emerged, that step type of economic indicators series influenced performance of algorithm. Therefore, one could see, how well the algorithm would perform if instead, interpolation between publication days would be used for those indicators. Note, that it was only a problem for data published less often than daily.

Finally, there could be a problem with dimension reduction. Here, PCA has been applied, but this is linear method - maximizes variation between data series, but using linear transformation. However, financial data may not be only linearly dependent, but also nonlinearly. During this transformation, nonlinearity might be removed thus some important information could be lost. Therefore, some nonlinear dimension reduction method could be applied, but one, which will not require long time to execute.

6.4 Final word

Finally, the project has been accomplished on time and within the scope that was expected. Despite the fact, that there are many areas for improvements, in its current state, it is able to outperform simple historical method for portfolio optimization.

I would like to mention, that work on this algorithm will not stop here, but will be continued until it has been proven, that it can perform well in the real life financial environment. This is expected to be long term research, even if not backed by academic institution.

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Appendices

.A Inputs for specific indices

.A.1 USA Economy - NASDAQ 100 and S&P 500

1. US AUTODATA RETAIL SALES OF NEW CARS: DOMESTIC (AR) VOLA
2. US AUTODATA RETAIL SALES OF NEW LIGHT TRUCKS: DOMESTIC (AR) VOLA
3. US AUTODATA RETAIL SALES OF NEW LIGHT VEHICLES: DOM. (AR) VOLA
4. US AUTODATA RETAIL SALES OF NEW LIGHT VEHICLES: TOTAL (AR) VOLA
5. US AVERAGE HOURLY EARN.PER WORKER IN MANUFACTURING INDUSTRY CURN
6. US AVG HOURLY REAL EARNINGS - PRIVATE NONFARM INDUSTRIES CONA
7. US AVG HRLY EARN - TOTAL PRIVATE NONFARM CURA
8. US AVG WKLY HOURS - TOTAL PRIVATE NONFARM VOLA
9. US BANKRUPTCY FILINGS, TOTAL BUSINESS (12 MO ENDING) VOLN
10. US BUSINESS INVENTORIES (MFG & TRADE) CURA
11. US BUSINESS SALES (MFG & TRADE) CURA
12. US CAPACITY UTILIZATION RATE - ALL INDUSTRY SADJ
13. US CAPITAL AND FINANCIAL ACCOUNT BALANCE CURA
14. US CHAIN-TYPE PRICE INDEX FOR PCE LESS FOOD & ENERGY (CORE) SADJ
15. US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADJ
16. US CHAIN-TYPE PRICE INDEX OF GDP SADJ
17. US CHALLENGER JOB-CUT ANNOUNCEMENTS VOLN
18. US CHANGE IN PRIVATE INVENTORIES (NIA) (AR) CURA
19. US CHANGE IN PRIVATE INVENTORIES (NIA) (AR) CONA
20. US CHICAGO PURCHASING MANAGER BUSINESS BAROMETER (SA) SADJ
21. US COMMERCIAL BANK ASSETS - COMMERCIAL & INDUSTRIAL LOANS CURA
22. US COMMERCIAL BANK ASSETS - LOANS & LEASES IN BANK CREDIT CURA
23. US CONSTRUCTION EXPENDITURES - TOTAL (AR) CURA
24. US CONSUMER CONFIDENCE INDEX SADJ
25. US CONSUMER CREDIT OUTSTANDING CURA
26. US CORPORATE PROFITS WITH IVA & CCADJ - TOTAL (AR) CURA
27. US CPI - ALL ITEMS LESS FOOD & ENERGY (CORE) SADJ
28. US CPI- ALL URBAN SAMPLE: ALL ITEMS - ANNUAL INFLATION RATE NADJ
29. US CPI - ALL URBAN: ALL ITEMS SADJ
30. US CURRENT ACCOUNT BALANCE CURA
31. US DISPOSABLE PERSONAL INCOME (MONTHLY SERIES) (AR) CURA
32. US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ
33. US ECI: COMPENSATION - CIVILIAN, ALL WORKERS SADJ
34. US EMPIRE STATE MFG SURVEY DIFFUSION INDEX-GENERAL BUS CONDITION
35. US EMPLOYED - NONFARM INDUSTRIES TOTAL (PAYROLL SURVEY) VOLA
36. US EXISTING HOME SALES: SINGLE-FAMILY & CONDO (AR) VOLA
37. US EXPORT PRICE INDEX - ALL COMMODITIES (END USE) NADJ
38. US EXPORTS F.A.S. CURA
39. US EXPORTS OF GOODS & SERVICES (NIA) (AR) CURA
40. US EXPORTS OF GOODS & SERVICES (NIA) (AR) CONA
41. US EXPORTS OF GOODS ON A BALANCE OF PAYMENTS BASIS CURA
42. US FEDERAL FUNDS RATE (MONTHLY AVERAGE)
43. US FEDERAL FUNDS TARGET RATE (EP)
44. US FEDERAL GOVERNMENT BUDGET BALANCE CURN
45. US FOREIGN NET LONG TERM FLOWS IN SECURITIES CURN
46. US FOREIGN RESERVE ASSETS CURN
47. US GDP - (AR) CURA
48. US GDP (AR) CONA
49. US GNP (AR) CURA
50. US GNP (AR) CONA
51. US GOODS & SERVICES BALANCE ON A BALANCE OF PAYMENTS BASIS CURA
52. US GOODS TRADE BALANCE ON A BALANCE OF PAYMENTS BASIS CURA
53. US GOVERNMENT CONSUMPTION & INVESTMENT (AR) CURA
54. US GOVERNMENT CONSUMPTION & INVESTMENT (AR) CONA
55. US IMPLICIT DEFLATOR - GDP SADJ
56. US IMPORT PRICE INDEX - ALL COMMODITIES (END USE) NADJ
57. US IMPORTS F.A.S. CURA
58. US IMPORTS OF GOODS & SERVICES (NIA) (AR) CONA
59. US IMPORTS OF GOODS & SERVICES (NIA) (AR) CURA
60. US IMPORTS OF GOODS ON A BALANCE OF PAYMENTS BASIS CURA
61. US INDEX OF HELP WANTED ADVERTISING VOLA
62. US INDUSTRIAL PRODUCTION - MANUFACTURING (NAICS) VOLA
63. US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA
64. US ISM PURCHASING MANAGERS INDEX (MFG SURVEY) SADJ
65. US JOB OPENINGS LEVEL - TOTAL VOLN
66. US MONETARY BASE CURA
67. US MONEY SUPPLY M1 CURA
68. US MONEY SUPPLY M2 (BCI 106) CONA
69. US NATIONAL ASSOCIATION OF HOME BUILDERS HOUSING MARKET INDEX
70. US NET INTERNATIONAL INVESTMENT POSITION OF US AT CURRENT COST
71. US NEW ORDERS - ALL MANUFACTURING INDUSTRIES CURA
72. US NEW ORDERS - MANUFACTURING, DURABLES CURA
73. US NEW ORDERS-MANUFACTURING, DURABLES, EXCL. TRANSPORTATION CURA
74. US NEW ORDERS - MANUFACTURING, EXCLUDING TRANSPORTATION CURA
75. US NEW PASSENGER CARS - TOTAL REGISTRATIONS VOLN
76. US NEW PRIVATE HOUSING UNITS AUTHORIZED BY BLDG.PERMIT (AR) VOLA
77. US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA
78. US OUTPUT PER HOUR OF ALL PERSONS - BUSINESS SECTOR SADJ
79. US OUTPUT PER HOUR OF ALL PERSONS - NONFARM BUSINESS SECTOR SADJ
80. US PENDING HOME SALES INDEX (AR) VOLA
81. US PERSONAL CONSUMPTION EXPENDITURES (MONTHLY SERIES) (AR) CURA
82. US PERSONAL CONSMPTN. EXPENDITURES (QUARTERLY SERIES) (AR) CURA
83. US PERSONAL CONSMPTN. EXPENDITURES (QUARTERLY SERIES) (AR) CONA
84. US PERSONAL INCOME (MONTHLY SERIES) (AR) CURA
85. US PERSONAL SAVING AS
86. US PHILADELPHIA FED OUTLOOK SURVEY-DIFFUSION INDEX,MFG. SADJ
87. US POPULATION (ESTIMATES USED IN NATIONAL ACCOUNTS) VOLN
88. US PPI - FINISHED GOODS SADJ
89. US PPI - FINISHED GOODS LESS FOODS & ENERGY (CORE) SADJ
90. US PRIME RATE CHARGED BY BANKS
91. US PRIVATE DOMESTIC FIXED INVESTMENT (AR) CURA
92. US PRIVATE DOMESTIC FIXED INVESTMENT (AR) CONA
93. US RETAIL SALES & FOOD SERVICES, TOTAL CURA
94. US RETAIL SALES & FOOD SVCS,TOTAL EXCL MOTOR VEH& PARTS DEALERS
95. US SALES BY MERCHANT WHOLESALERS - TOTAL CURA
96. US SALES OF NEW ONE FAMILY HOUSES (AR) VOLA
97. US TERMS OF TRADE REBASED TO 1975=100 NADJ
98. US THE CONFERENCE BOARD LEADING ECONOMIC INDICATORS INDEX SADJ
99. US TIPP ECONOMIC OPTIMISM INDEX: OVERALL NADJ
100. US TOTAL CIVILIAN EMPLOYMENT VOLA
101. TOTAL MTG APPS INDEX - MARKET (SA) - ES
102. US TOTAL TREASURY SECURITIES OUTSTANDING (PUBLICDEBT) CURN
103. US TRADE-WEIGHTED VALUE OF US DOLLAR AGAINST MAJOR CURRENCIES
104. US TREASURY BILL RATE - 3 MONTH (EP)
105. US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 20 YEAR
106. US UNEMPLOYED - (16 YRS & OVER) VOLA
107. US UNEMPLOYMENT RATE SADJ
108. US UNIT LABOR COSTS - BUSINESS SECTOR SADJ
109. US UNIT LABOR COSTS - NONFARM BUSINESS SECTOR SADJ
110. US UNIVERSITY OF MICHIGAN CONSUMER SENTIMENT INDEX VOLN
111. US US $ TO EURO NOON NY (EP) NADJ
112. US US 3 MONTH INTERBANK RATE (LONDON) (MTH.AVG.)
113. US UNEMPLOYMENT (SA) - INITIAL CLAIMS - ES

114. US VISIBLE TRADE BALANCE F.A.S.-F.A.S. CURA
115. US WHOLESALE TRADE INVENTORIES - TOTAL CURA
116. ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE - U$/BL
117. CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE - U$/TO
118. POLISH ZLOTY TO EURO (WMR) - EXCHANGE RATE
119. POLISH ZLOTY TO 100 JAPANESE YEN(PO) - EXCHANGE RATE
120. POLISH ZLOTY TO UK £(WMR) - EXCHANGE RATE
121. POLISH ZLOTY TO US $ (GTIS) - EXCHANGE RATE
122. EURO TO UK £(WMR&DS) - EXCHANGE RATE
123. EURO TO US $ (WMR&DS) - EXCHANGE RATE
124. EURO TO UK £1M FWD (WMR) - EXCHANGE RATE
125. EURO TO UK £1Y FWD (WMR) - EXCHANGE RATE
126. EURO TO UK £1W FWD (WMR) - EXCHANGE RATE
127. EURO TO US $ 1M FWD (BBI) - EXCHANGE RATE
128. EURO TO US $ 1Y FWD (BBI) - EXCHANGE RATE
129. US $ TO JAPANESE YEN (JPM) - EXCHANGE RATE
130. US $ TO HONG KONG $ (GTIS) - EXCHANGE RATE
131. UK £TO US $ (WMR) - EXCHANGE RATE
132. DAX 30 PERFORMANCE - PRICE INDEX
133. DOW JONES INDUSTRIALS - PRICE INDEX
134. FRANCE CAC 40 - PRICE INDEX
135. FTSE 100 - PRICE INDEX
136. HANG SENG - PRICE INDEX
137. NIKKEI 225 STOCK AVERAGE - PRICE INDEX
138. NASDAQ 100 - PRICE INDEX
139. WARSAW GENERAL INDEX 20 - PRICE INDEX
140. S&P 500 COMPOSITE - PRICE INDEX

.A.2 UK Economy - FTSE 100

1. UK 3 MONTHS TREASURY BILLS YIELD (EP)
2. UK AEI: WHOLE ECONOMY INCL.BONUS -
3. UK AVERAGE EARNINGS INDEX GB: WHOLE ECONOMY SADJ
4. UK BALANCE OF PAYMENTS: CURRENT ACCOUNT BALANCE CURA
5. UK BALANCE OF PAYMENTS: FINANCIAL& CAPITAL ACCOUNT BALANCE CURN
6. UK BOP: EXPORTS - TRADE IN GOODS& SERVICES CONA
7. UK BANK AND BUILDING SOCIETY LENDING TOTAL CURA
8. UK BANK OF ENGLAND BASE RATE (EP)
9. UK BOP: (EU 27 TRADE) BALANCE - TRADE IN GOODS CURA
10. UK CBI DIST. TRADES: VOLUME OF SALES EXPECTED NADJ
11. UK CBI ENQUIRY:
12. UK CBI ENQUIRY: BUSINESS OPTIMISM NADJ
13. UK CBI MONTHLY ENQUIRY: ORDER BOOK VOLUME - BALANCE NADJ
14. UK CBI RETAILING: VOLUME OF SALES REPORTED NADJ
15. UK CHANGES IN INVENTORIES INCLUDING ALIGNMENT ADJUSTMENT CURA
16. UK CHANGES IN INVENTORIES INCLUDING ALIGNMENT ADJUSTMENT(CVM)
17. UK COMPANY INSOLVENCIES VOLA
18. UK COMPOSITE LEADING INDICATOR (TREND RESTORED)
19. UK CONSUMER CONFIDENCE INDICATOR - UK SADJ
20. UK CONSUMER SPENDING CURA
21. UK CONSUMER SPENDING (CVM) CONA
22. UK CPI-HARMONISED EUROPEAN UNION BASIS EST.D PRE-97 2005=100
23. UK CPI INDEX: EXCL. ENERGY& SEASONAL FOOD (SP) 2005=100 NADJ
24. UK EXPORT PRICE INDEX - BALANCE OF PAYMENTS BASISNADJ
25. UK EXPORTS CURN
26. UK EXPORTS - BALANCE OF PAYMENTS BASIS CURA
27. UK EXPORTS OF GOODS AND SERVICES CURA
28. UK EXPORTS OF GOODS AND SERVICES (CVM) CONA
29. UK FINAL CON.EXP.OF NON PROFIT INSTITUTIONS SERVING HOUSEHOLDS(C
30. UK FINAL CONS.EXPEND OF NON PROFIT INSTITUTIONS SERVING HOUSEHOL
31. UK FINAL CONSUMPTION EXPENDITURE - HOUSEHOLDS CURA
32. UK FINAL CONSUMPTION EXPENDITURE - HOUSEHOLDS (CVM) CONA
33. UK FT ALL SHARE INDEX (EP) NADJ
34. UK GBP STERLING EFFECTIVE EXCHANGE RATE INDEX (2005=100) NADJ
35. UK GDP AT MARKET PRICES CURA
36. UK GDP AT MARKET PRICES (CVM) CONA
37. UK GDP: CONST.PRICE: SEASONALLY ADJUSTED,NEW CHAINWEIGHTED CONA
38. UK GENERAL GOVERNMENT: FINAL CONSUMPTION EXPENDITURE CURA
39. UK GENERAL GOVERNMENT: FINAL CONSUMPTION EXPENDITURE(CVM) CONA
40. UK GFCF CURA
41. UK GFCF (CVM) CONA
42. UK GROSS NATIONAL INCOME CURA
43. UK GROSS REDEMPTION YIELD ON 20 YEAR GILTS (PERIODAVERAGE)
44. UK HOUSEBUILDING STARTED IN GREAT BRITAIN - TOTALVOLN
45. UK HOUSEHOLD SAVINGS RATIO SADJ
46. UK HOUSEHOLDS' DISPOSABLE INCOME CONA
47. UK IMPORT PRICE INDEX - BALANCE OF PAYMENTS BASISNADJ
48. UK IMPORTS CURN
49. UK IMPORTS - BALANCE OF PAYMENTS BASIS CURA
50. UK BOP: IMPORTS - TRADE IN GOODS& SERVICES CONA
51. UK IMPORTS OF GOODS AND SERVICES CURA
52. UK IMPORTS OF GOODS AND SERVICES (CVM) CONA
53. UK INDUSTRIAL PRODUCTION INDEX VOLA
54. UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA
55. UK RPI- INFLATION RATE
56. UK INFLATION RATE FOR HARMONISED CPI
57. UK INTERBANK RATE - 3 MONTH (MTH.AVG.)
58. UK IPD OF GDP MARKET PRICES SADJ
59. UK JP MORGAN TRADE WEIGHTED INDEX UK, REAL,BROAD BASIS NADJ
60. UK LFS: UNEMPLOYMENT RATE, ALL, AGED 16& OVER SADJ
61. UK LOANS ON DWELLINGS APPROVED VOLA
62. UK MAJOR BANKS PRIME LENDING RATE (EP)
63. UK MONEY SUPPLY M0: NOTES& COINS IN CIRC.OUTSIDEBANK OF ENGLAN
64. UK MONEY SUPPLY M1 (ESTIMATE OF EMU AGGREGATE FORTHE UK) CURA
65. UK MONEY SUPPLY M2: RETAIL DEPOSITS AND CASH IN M4 (EP) CURA
66. UK MONEY SUPPLY M4 (EP) CURA
67. UK NATIONWIDE MONTHLY AVE. HOUSE PRICE INDEX (SEAS. ADJ.) SADJ
68. UK NET INTERNATIONAL INVESTMENT POSITION CURN
69. UK NEW ORDERS OBTAINED - NEW CONSTRUCTION WORK (TOTAL) CONA
70. UK NON-EU(2004):BOP:BALANCE:SA:TOTAL TRADE IN GOODS CURA
71. UK PERSONAL BORROWING: NET LENDING-SECURED ON DWELLINGS(SA) CURA
72. UK PPI - OUTPUT OF MANUFACTURED PRODUCTS (HOME SALES) NADJ
73. UK PPI NET SECTOR INPUT: ALL MFG. INCL. CLIMATE CHANGE LEVY NADJ
74. UK PPI: PRDS. OF MFG. INDUSTRY EXCL.F, B, P& T NADJ
75. UK PRODUCTIVITY - WHOLE ECONOMY SADJ
76. UK PUBLIC SECTOR NET CASH REQUIREMENT CURN
77. UK PUBLIC SECTOR NET CASH REQUIREMENT CURN
78. UK PUBLIC SECTOR: TOTAL NET BORROWING CURN
79. UK RESIDENT POPULATION: UK
80. UK RETAIL SALES (MONTHLY ESTIMATE, DS CALCULATED)CURA
81. UK RETAIL SALES: ALL RETAILERS - ALL BUSINESS VOLA
82. UK RPI NADJ
83. UK RPI NADJ
84. UK RPI - ALL ITEMS EXCLUDING MORTGAGE INTEREST NADJ
85. UK TERMS OF TRADE - EXPORT/IMPORT PRICES (BOP BASIS) NADJ
86. UK TOTAL CONSUMER CREDIT: AMOUNT OUTSTANDING CURA
87. UK TOTAL CONSUMER CREDIT: NET LENDING: SA CURA
88. UK TOTAL GROSS OPERATING SURPLUS OF CORPORATIONS CURA
89. UK TOTAL GROSS OPERATING SURPLUS OF CORPORATIONS CURA
90. UK UK CAR REGISTRATIONS VOLN
91. UK UK GOVERNMENT GROSS RESERVE ASSETS (EP) CURN
92. UK UK MONEY SUPPLY M3(ESTIMATE OF EMU AGGREGATE FOR THE UK) CURA
93. UK UNEMPLOYMENT CLAIMANT COUNT VOLA
94. UK UNEMPLOYMENT RATE SADJ
95. UK UNIT LABOUR COST INDEX - WHOLE ECONOMY SADJ

96. UK US $ TO ?1
97. UK VISIBLE TRADE BALANCE CURN
98. UK VISIBLE TRADE BALANCE - BALANCE OF PAYMENTS BASIS CURA
99. UK WAGE EARNINGS IN MANUFACTURING INDEX SADJ
100. UK WORKFORCE JOBS - UK VOLA
101. ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE - U $ BL
102. CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE - U $ /TO
103. POLISH ZLOTY TO EURO (WMR) - EXCHANGE RATE
104. POLISH ZLOTY TO 100 JAPANESE YEN(PO) - EXCHANGE RATE
105. POLISH ZLOTY TO UK ? (WMR) - EXCHANGE RATE
106. POLISH ZLOTY TO US $ (GTIS) - EXCHANGE RATE
107. EURO TO UK ? (WMR&DS) - EXCHANGE RATE
108. EURO TO US $ (WMR&DS) - EXCHANGE RATE
109. EURO TO UK ? 1M FWD (WMR) - EXCHANGE RATE
110. EURO TO UK ? 1Y FWD (WMR) - EXCHANGE RATE
111. EURO TO UK ? 1W FWD (WMR) - EXCHANGE RATE
112. EURO TO US $ 1M FWD (BBI) - EXCHANGE RATE
113. EURO TO US $ 1Y FWD (BBI) - EXCHANGE RATE
114. US $ TO JAPANESE YEN (JPM) - EXCHANGE RATE
115. US $ TO HONG KONG$ (GTIS) - EXCHANGE RATE
116. UK ? TO US $ (WMR) - EXCHANGE RATE
117. DAX 30 PERFORMANCE - PRICE INDEX
118. DOW JONES INDUSTRIALS - PRICE INDEX
119. FRANCE CAC 40 - PRICE INDEX
120. FTSE 100 - PRICE INDEX
121. HANG SENG - PRICE INDEX
122. NIKKEI 225 STOCK AVERAGE - PRICE INDEX
123. NASDAQ 100 - PRICE INDEX
124. WARSAW GENERAL INDEX 20 - PRICE INDEX
125. S&P 500 COMPOSITE - PRICE INDEX

.A.3 Polish Economy - WIG 20

1. PO AVERAGE MONTHLY WAGE (GROSS) CURN
2. PO AVERAGE MONTHLY WAGE (GROSS) (
3. PO BOP: BALANCE OF GOODS (TRANSACTION BASIS, EUR)CURN
4. PO BOP: CAPITAL AND FINANCIAL ACCOUNT BALANCE CURN
5. PO BOP: GOODS EXPORTS (TRANSACTION BASIS, EUR) CURN
6. PO BOP: GOODS IMPORTS (TRANSACTION BASIS, EUR) CURN
7. PO BUSINESS CONFIDENCE: MANUFACTURING - BALANCE OF OPINION SADJ
8. PO CHANGES IN INVENTORIES CURN
9. PO CHANGES IN INVENTORIES CONN
10. PO CHANGES IN INVENTORIES (CURRENT) CURN
11. PO CONSUMER CONFIDENCE INDICATOR - POLAND SADJ
12. PO CONSUMER CREDIT CURN
13. PO CONSUMER SPENDING (CURRENT) CURN
14. PO CPI NADJ
15. PO CPI - ALL ITEMS NADJ
16. PO CPI - ALL ITEMS (
17. PO CURRENT ACCOUNT BALANCE (TRANSACTION BASIS, EUR) CURN
18. PO DISCOUNT RATE - CENTRAL BANK
19. PO DWELLINGS COMPLETED VOLN
20. PO EMPLOYEES VOLN
21. PO EMPLOYEES (
22. PO EMPLOYMENT IN PRIVATE SECTOR - TOTAL VOLN
23. PO EMPLOYMENT IN PRIVATE SECTOR - TOTAL (
24. PO EXPORT UNIT VALUE INDEX NADJ
25. PO EXPORTS CURN
26. PO EXPORTS - GOODS AND SERVICES CURN
27. PO EXPORTS (
28. PO EXTERNAL BALANCE OF PRODUCT CURN
29. PO EXTERNAL BALANCE OF PRODUCT CONN
30. PO GDP CURN
31. PO GDP CONN
32. PO GDP - GENERAL GOVERNMENT & NPISH CONSUMPTION EXPENDITURE CURN
33. PO GDP - GENERAL GOVERNMENT & NPISH CONSUMPTION EXPENDITURE CONN
34. PO GDP-GENERAL GOVT. & NPISH CONSUMPTION EXPENDITURE (
35. PO GDP-GENERAL GOVT. & NPISH CONSUMPTION EXPENDITURE (
36. PO GDP - GOVERNMENT AND NPISH EXPENDITURE CURN
37. PO GDP - INDIVIDUAL CONSUMPTION EXPENDITURE VOLN
38. PO GDP - INDIVIDUAL CONSUMPTION EXPENDITURE CURN
39. PO GDP - INDIVIDUAL CONSUMPTION EXPENDITURE CONN
40. PO GDP - INDIVIDUAL CONSUMPTION EXPENDITURE (
41. PO GDP - INDIVIDUAL CONSUMPTION EXPENDITURE (
42. PO GDP
43. PO GDP (
44. PO GDP (CURRENT) CURN
45. PO GFCF CURN
46. PO GFCF CONN
47. PO GFCF (CURRENT) CURN
48. PO GROSS EXTERNAL DEBT CURN
49. PO GROSS MONTHLY WAGES IN MANUFACTURING CURN
50. PO GROSS MONTHLY WAGES IN MANUFACTURING (
51. PO IMPORT UNIT VALUE INDEX NADJ
52. PO IMPORTS CURN
53. PO IMPORTS - GOODS AND SERVICES CURN
54. PO IMPORTS (
55. PO INDUSTRIAL PRODUCTION VOLN
56. PO INDUSTRIAL PRODUCTION (
57. PO IPD: GDP CONA
58. PO MONEY MARKET OFFER RATE - 3 MONTH
59. PO MONEY SUPPLY: M0 CURN
60. PO MONEY SUPPLY: M0 (EP) CURA
61. PO MONEY SUPPLY: M1 (EP) CURA
62. PO MONEY SUPPLY: M1 (ESCB DEFINITION FROM DEC.1996) CURN
63. PO MONEY SUPPLY: M2 (ESCB DEFINITION FROM DEC.1996) CURN
64. PO MONEY SUPPLY: M3 (ECB DEFINITION) CURN
65. PO MONEY SUPPLY: M3 (EP) CURA
66. PO OFFICIAL RESERVE ASSETS CURN
67. PO POLISH ZLOTY TO US $ (AVERAGE)
68. PO POPULATION VOLN
69. PO PPI NADJ
70. PO PPI - INDUSTRY NADJ
71. PO PPI - INDUSTRY (
72. PO PROFITABILITY RATES OF NET TURNOVER
73. PO REFERENCE RATE - INTERVENTION RATE OPEN MONEY MARKET
74. PO RETAIL SALES NADJ
75. PO STATE BUDGET BALANCE (SURPLUS/DEFICIT) CURN
76. PO TERMS OF TRADE INDEX NADJ
77. PO TREASURY BILL YIELD - 13 WEEK
78. PO UNEMPLOYMENT VOLN
79. PO UNEMPLOYMENT RATE NADJ
80. PO VISIBLE TRADE BALANCE CURN
81. PO WARSAW GENERAL SHARE PRICE INDEX (EP) NADJ
82. ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE - U$/BL
83. CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE - U$/TO
84. POLISH ZLOTY TO EURO (WMR) - EXCHANGE RATE
85. POLISH ZLOTY TO 100 JAPANESE YEN(PO) - EXCHANGE RATE
86. POLISH ZLOTY TO UK ? (WMR) - EXCHANGE RATE
87. POLISH ZLOTY TO US $ (GTIS) - EXCHANGE RATE
88. EURO TO UK ? (WMR&DS) - EXCHANGE RATE
89. EURO TO US $ (WMR&DS) - EXCHANGE RATE
90. EURO TO UK ? 1M FWD (WMR) - EXCHANGE RATE
91. EURO TO UK ? 1Y FWD (WMR) - EXCHANGE RATE
92. EURO TO UK ? 1W FWD (WMR) - EXCHANGE RATE
93. EURO TO US $ 1M FWD (BBI) - EXCHANGE RATE
94. EURO TO US $ 1Y FWD (BBI) - EXCHANGE RATE
95. US $ TO JAPANESE YEN (JPM) - EXCHANGE RATE
96. US $ TO HONG KONG $ (GTIS) - EXCHANGE RATE
97. UK ? TO US $ (WMR) - EXCHANGE RATE
98. DAX 30 PERFORMANCE - PRICE INDEX
99. DOW JONES INDUSTRIALS - PRICE INDEX
100. FRANCE CAC 40 - PRICE INDEX
101. FTSE 100 - PRICE INDEX
102. HANG SENG - PRICE INDEX
103. NIKKEI 225 STOCK AVERAGE - PRICE INDEX
104. NASDAQ 100 - PRICE INDEX
105. WARSAW GENERAL INDEX 20 - PRICE INDEX
106. S&P 500 COMPOSITE - PRICE INDEX

.A.4 Japanese Economy - NIKKEI 225

1. JP 3 MONTH INTERBANK RATE (EP)
2. JP AGGREGATE BANK LENDING (EXCL. SHINKIN BANKS) CURN
3. JP ALL INDUSTRIES ACTIVITY INDEX SADJ
4. JP ALL INDUSTRIES ACTIVITY INDEX NADJ
5. JP AVERAGE MONTHLY CASH EARN.- MANUFACTURING(SEE JPTEMFROA) CURN
6. JP BASIC DISCOUNT & LOAN RATE (ODR PRIOR TO JAN 01)
7. JP BOP: CAPITAL & FINANCIAL ACCOUNT BALANCE CURN
8. JP BOP: CURRENT ACCOUNT BALANCE CURA
9. JP BOP: CURRENT ACCOUNT BALANCE (DS CALC BEFORE 1985) CURN
10. JP BOP: EXPORTS OF GOODS CURA
11. JP BOP: IMPORTS OF GOODS CURA
12. JP BOP: VISIBLE TRADE BALANCE CURA
13. JP BUSINESS FAILURES VOLN
14. JP CHANGES IN STOCKS CURA
15. JP CHANGES IN STOCKS (AR) CONA
16. JP COINCIDENT COMPOSITE INDEX
17. JP COINCIDENT DIFFUSION INDEX
18. JP CONSTRUCTION WORKS: NEW ORDERS CURN
19. JP CONSUMER CONFIDENCE INDEX SADJ
20. JP CORPORATE GOODS PRICE INDEX: DOMESTIC - ALL COMMODITIES NADJ
21. JP CPI EXCLUDING FOOD & ENERGY - TOKYO (CORE) NADJ
22. JP CPI EXCLUDING FOOD & ENERGY (CORE) NADJ
23. JP CPI EXCLUDING FOOD & ENERGY (CORE) SADJ
24. JP CPI: NATIONAL MEASURE NADJ
25. JP CPI: NATIONAL MEASURE SADJ
26. JP CPI: NATIONAL MEASURE - ANNUAL INFLATION RATE NADJ
27. JP CPI: TOKYO MEASURE SADJ
28. JP DEFLATOR - GDP SADJ
29. JP EMPLOYED PERSONS VOLA
30. JP EMPLOYED PERSONS VOLN
31. JP EMPLOYED PERSONS - MANUFACTURING VOLN
32. JP EMPLOYED PERSONS - NON AGRICULTURE & FORESTRY VOLA
33. JP EMPLOYEE - NON-AGRICULTURE & FORESTRY VOLN
34. JP EXPORT PRICE INDEX - ALL COMMODITIES NADJ
35. JP EXPORTS OF GOODS - CUSTOMS BASIS CURA
36. JP EXPORTS OF GOODS & SERVICES (AR) CURA
37. JP EXPORTS OF GOODS & SERVICES (AR) CONA
38. JP GDFCF (AR) CURA
39. JP GDFCF (AR) CONA
40. JP GDP (AR) CURA
41. JP GDP (AR) CONA
42. JP GNI (AR) CURA
43. JP GNI (AR) CONA
44. JP GOLD AND FOREIGN EXCHANGE RESERVES CURN
45. JP GOVERNMENT CONSUMPTION EXPENDITURE (AR) CURA
46. JP GOVERNMENT CONSUMPTION EXPENDITURE (AR) CONA
47. JP IMPORT PRICE INDEX - ALL COMMODITIES NADJ
48. JP IMPORTS OF GOODS - CUSTOMS BASIS CURA
49. JP IMPORTS OF GOODS & SERVICES (AR) CURA
50. JP IMPORTS OF GOODS & SERVICES (AR) CONA
51. JP INCORPORATED BUSINESS: CURRENT PROFITS - ALL INDUSTRIES CURN
52. JP INDUSTRIAL PRODUCTION - MANUFACTURING VOLA
53. JP INDUSTRIAL PRODUCTION - MANUFACTURING VOLN
54. JP INDUSTRIAL PRODUCTION - MINING & MANUFACTURINGVOLA
55. JP INDUSTRIAL PRODUCTION - MINING & MANUFACTURINGVOLN
56. JP INTEREST-BEARING GOVERNMENT BONDS - 10-YEAR (EP)
57. JP JAPANESE YEN EFFECTIVE EXCHANGE RATE INDEX NADJ
58. JP JAPANESE YEN REAL EFFECTIVE EXCHANGE RATE INDEX (BOJ) NADJ
59. JP JAPANESE YEN TO US $
60. JP JOB OFFERS TO APPLICANTS RATIO SADJ
61. JP LABOR PRODUCTIVITY INDEX - ALL INDUSTRIES SADJ
62. JP LABOUR FORCE PARTICIPATION RATE NADJ
63. JP LAGGING COMPOSITE INDEX
64. JP LEADING COMPOSITE INDEX
65. JP LEADING DIFFUSION INDEX
66. JP LIVING EXPND. INDEX - REAL (INCL. AFF) SADJ
67. JP MACHINERY ORDERS CURA
68. JP MACHINERY ORDERS: DOM. - PRIVATE (EXCL. VOLATILE ORDERS) CURN
69. JP MACHINERY ORDERS: DOM. - PRIVATE (EXCL. VOLATILE ORDERS) CURA
70. JP MACHINERY ORDERS: DOM.DEMAND-PRIVATE DEMAND (EXCL. SHIP) CURA
71. JP MONEY SUPPLY: L (METHO-BREAK, APR. 2003) CURA
72. JP MONEY SUPPLY: M0 - CASH CIRCL. (METHO-BREAK, APR.03) CURN
73. JP MONEY SUPPLY: M1 (METHO-BREAK, APR. 2003) CURN
74. JP MONEY SUPPLY: M2 (METHO-BREAK, APR. 2003) CURN
75. JP MONEY SUPPLY: M2 (METHO-BREAK, APR. 2003) CURA
76. JP MONEY SUPPLY: M4 BROAD LIQUIDITY CURN
77. JP MONTHLY WORKERS SAVINGS & INSURANCE RATE
78. JP MOTOR VEHICLE NEW REGISTRATIONS: PASSENGER CARS EXCL.BELOW 66
79. JP NET INTERNATIONAL INVESTMENT POSITION
80. JP NEW HOUSING CONSTRUCTION STARTED VOLA
81. JP NEW HOUSING CONSTRUCTION STARTED VOLN
82. JP OPERATING RATIO - MANUFACTURING SADJ
83. JP OUTLOOK SVY.OF LARGE CO.ON IND.BUS.CNDTNS,ACTL(DS CALC.) SADJ
84. JP OVERNIGHT CALL MONEY RATE, UNCOLLATERALISED (EP)
85. JP OVERNIGHT UNCOLLATERISED CALL MONEY RATE (AVG.)
86. JP PERSONAL CONSUMPTION EXPENDITURE (AR) CURA
87. JP PRIME RATE - LONG TERM (EP)
88. JP PRIVATE CONSUMPTION EXPENDITURE (AR) CONA
89. JP RETAIL SALES CURN
90. JP RETAIL SALES INDEX SADJ
91. JP RETAIL SALES INDEX NADJ
92. JP SURPLUS OR DEFICIT - CENTRAL GOVERNMENT
93. JP SURPLUS OR DEFICIT - CENTRAL GOVERNMENT CURN
94. JP TANKAN: BUS. CNDTN. - ALL ENTPS., IND., ACTL. NADJ
95. JP TANKAN: BUS. CNDTN. - LARGE ENTPS., MFG., ACTL. NADJ
96. JP TANKAN: BUS. CNDTN. - LARGE ENTPS., NON-MFG., ACTL. NADJ
97. JP TANKAN: BUS. CNDTN. - SMALL ENTPS., MFG., ACTL. NADJ
98. JP TERMS OF TRADE INDEX NADJ
99. JP TERTIARY INDUSTRY ACTIVITY INDEX SADJ
100. JP TERTIARY INDUSTRY ACTIVITY INDEX NADJ
101. JP TOKYO STOCK EXCHANGE - TOPIX (EP) NADJ
102. JP UNEMPLOYED SEEKING EMPLOYMENT VOLN
103. JP UNEMPLOYMENT LEVEL VOLA
104. JP UNEMPLOYMENT RATE SADJ
105. JP UNEMPLOYMENT RATE NADJ
106. JP UNFILLED VACANCIES: NEW JOB OFFERS VOLA
107. JP VISIBLE TRADE BALANCE - CUSTOMS BASIS CURA
108. JP WAGE INDEX: CASH EARNINGS - ALL INDUSTRIES SADJ
109. JP WAGE INDEX: CONT. CASH EARNINGS - MANUFACTURING SADJ
110. JP WORKERS HH LIVING EXPND. INDEX (INCL. AFF) SADJ
111. JP WORKERS HOUSEHOLD LIVING EXPENDITURE (INCL. AFF) CURN
112. ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE - U$/BL
113. CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE - U$/TO
114. POLISH ZLOTY TO EURO (WMR) - EXCHANGE RATE
115. POLISH ZLOTY TO 100 JAPANESE YEN(PO) - EXCHANGE RATE
116. POLISH ZLOTY TO UK ? (WMR) - EXCHANGE RATE
117. POLISH ZLOTY TO US $ (GTIS) - EXCHANGE RATE
118. EURO TO UK ? (WMR&DS) - EXCHANGE RATE
119. EURO TO US $ (WMR&DS) - EXCHANGE RATE
120. EURO TO UK ? 1M FWD (WMR) - EXCHANGE RATE
121. EURO TO UK ? 1Y FWD (WMR) - EXCHANGE RATE
122. EURO TO UK ? 1W FWD (WMR) - EXCHANGE RATE
123. EURO TO US $ 1M FWD (BBI) - EXCHANGE RATE
124. EURO TO US $ 1Y FWD (BBI) - EXCHANGE RATE
125. US $ TO JAPANESE YEN (JPM) - EXCHANGE RATE
126. US $ TO HONG KONG $ (GTIS) - EXCHANGE RATE
127. UK ? TO US $ (WMR) - EXCHANGE RATE
128. DAX 30 PERFORMANCE - PRICE INDEX
129. DOW JONES INDUSTRIALS - PRICE INDEX
130. FRANCE CAC 40 - PRICE INDEX
131. FTSE 100 - PRICE INDEX
132. HANG SENG - PRICE INDEX
133. NIKKEI 225 STOCK AVERAGE - PRICE INDEX
134. NASDAQ 100 - PRICE INDEX
135. WARSAW GENERAL INDEX 20 - PRICE INDEX
136. S&P 500 COMPOSITE - PRICE INDEX

.A.5 German Economy - DAX

1. BD ASSESSMENT OF BUSINESS SITUATION (PAN GERMANY)SADJ
2. BD BANK LENDING TO INDIVIDUALS (EXCLUDING HOUSINGLOANS) CURN
3. BD BANK PRIME LENDING RATE / ECB MARGINAL LENDING FACILITY
4. BD BOP CAPITAL AND FINANCIAL ACCOUNT BALANCE (PANBD M0790) CURN
5. BD BUSINESS CLIMATE INDEX (PAN GERMANY) SADJ
6. BD BUSINESS EXPECTATIONS (PAN GERMANY) SADJ
7. BD BUSINESS EXPECTATIONS (PAN GERMANY) SADJ
8. BD BUSINESS EXPECTATIONS (PAN GERMANY) (
9. BD CAPACITY UTILISATION-MFG. (FOR WG SEE WGCAPUTLQ) SADJ
10. BD CHAIN-TYPE PRICE INDEX - GDP NADJ
11. BD CHAIN-TYPE QUANTITY INDEX OF GDP SADJ
12. BD CHANGE OF STOCKS CURA
13. BD CONSTRUCTION ORDERS RECEIVED - RESIDENTIAL BUILDINGS VOLA
14. BD CONSUMER CONFIDENCE INDICATOR SADJ
15. BD CONSUMER EXPENDITURE - RATE OF CHANGE IN REAL TERMS CONA
16. BD CONSUMER EXPENDITURE CURA
17. BD CONSUMER EXPENDITURE CONA
18. BD CONSUMERS CONFIDENCE INDEX SADJ
19. BD CPI SADJ
20. BD CPI - HARMONISED EUROPEAN UNION BASIS (2005=100) NADJ
21. BD CPI - NIEDERSACHSEN (SEE BDCONONSF FOR 2000=100) NADJ
22. BD CPI (
23. BD CPI (EXCLUDING ENERGY AND SEASONAL FOOD) NADJ
24. BD CPI (PAN BD FROM 1991) NADJ
25. BD CURRENT ACCOUNT BALANCE CURN
26. BD DAX SHARE PRICE INDEX, EP NADJ
27. BD DISCOUNT RATE / SHORT TERM EURO REPO RATE (MTH.AVG.)
28. BD DISPOSABLE INCOME (PAN BD Q0191) CURA
29. BD EMPLOYED PERSONS (RESIDENCE CONCEPT) ((
30. BD EMPLOYED PERSONS (RESIDENCE CONCEPT, ILO) VOLA
31. BD EMPLOYED PERSONS (WORK-PLACE CONCEPT) VOLA
32. BD EXPORT PRICE INDEX SADJ
33. BD EXPORTS (TRADE VOLUME ON 2005 BASIS) CONA
34. BD EXPORTS FOB (PAN BD M0790) CURA
35. BD EXPORTS FOB (PAN BD M0790) (
36. BD EXPORTS FOB. CURA
37. BD EXPORTS OF GOODS & SERVICES CURA
38. BD EXPORTS OF GOODS & SERVICES CONA
39. BD FEDERAL/LANDER GOVERNMENT DEFICIT/SURPLUS CURN
40. BD FIBOR - 3 MONTH (MTH.AVG.)
41. BD FIXED INVESTMENT CURA
42. BD FIXED INVESTMENT CONA
43. BD GDP CONA
44. BD GDP - IPD SADJ
45. BD GDP - IPD (
46. BD GDP - RATE OF CHANGE IN REAL TERMS (
47. BD GDP (PAN BD FROM 1991) CURA
48. BD GERMAN MARKS TO US$ (MTH.AVG.)
49. BD GFK CONSUMER CLIMATE SURVEY - KONSUMKLIMA SADJ
50. BD GNI CURA
51. BD GOVERNMENT CONSUMPTION - RATE OF CHANGE IN REAL TERMS CONA
52. BD GOVERNMENT CONSUMPTION CURA
53. BD GOVERNMENT CONSUMPTION CONA
54. BD GROSS ENTREPRENEURIAL AND PROPERTY INCOME CURA
55. BD GROSS VALUE ADDED, TOTAL - CHAIN-TYPE QUANTITY INDEX SADJ
56. BD IFO BUSINESS CLIMATE INDEX (PAN GERMANY) SADJ
57. BD IMPORT PRICE INDEX SADJ
58. BD IMPORTS (TRADE VOLUME ON 2005 BASIS) CONA
59. BD IMPORTS CIF CURA
60. BD IMPORTS CIF (PAN BD M0790) CURA
61. BD IMPORTS CIF (PAN BD M0790) (
62. BD IMPORTS OF GOODS & SERVICES CURA
63. BD IMPORTS OF GOODS & SERVICES CONA
64. BD INDUSTRIAL PRODUCTION INCLUDING CONSTRUCTION VOLA
65. BD INDUSTRIAL PRODUCTION INCLUDING CONSTRUCTION (
66. BD INDUSTRIAL PRODUCTION: MANUFACTURING VOLA
67. BD INFLATION
68. BD LENDING TO ENTERPRISES & INDIVIDUALS CURN
69. BD LONG TERM GOVERNMENT BOND YIELD (9-10 YEARS MATURITY)
70. BD MANUFACTURING ORDERS VOLA
71. BD MANUFACTURING ORDERS SADJ
72. BD MONEY SUPPLY-GERMAN CONTRIBUTION TO EURO M1(PAN BD M0790)
73. BD MONEY SUPPLY- M2 (CONTRIBUTION TO EURO BASIS FROM M0195) CURA
74. BD MONEY SUPPLY- M3 (CONTRIBUTION TO EURO BASIS FROM M0195) CURA
75. BD MONEY SUPPLY-M3(CONTRIBUTION TO EURO BASIS FROM M0195)(
76. BD MONEY SUPPLY M0 CURN
77. BD NET EXTERNAL POSITION OF THE BUNDESBANK CURN
78. BD NEW REGISTRATIONS - CARS VOLN
79. BD PERSONAL SAVINGS (PAN BD Q0191) CURA
80. BD PERSONAL SAVINGS RATIO (PAN BD Q0191) SADJ
81. BD POPULATION (31.DEC FROM 2003 - PAN BD FROM 1991) VOLN
82. BD POPULATION (PAN BD FROM 1991) VOLN
83. BD PPI - INDUSTRIAL PRODUCTS (
84. BD PPI: INDL. PRODUCTS, TOTAL, SOLD ON THE DOMESTIC MARKET NADJ
85. BD PRODUCER PRICES - INDUSTRIAL PRODUCTS SADJ
86. BD PRODUCTIVITY & LABOUR COSTS: LABOUR COSTS PER UNIT OF OUTPUT
87. BD PRODUCTIVITY: OUTPUT PER MAN-HOUR IN IND. (SUSP.) (
88. BD PRODUCTIVITY: OUTPUT PER MAN-HOUR WORKED IN INDUSTRY SADJ
89. BD RESERVES - MONETARY: TOTAL CURN
90. BD RETAIL SALES EXCL.CARS-X-12-ARIMA(EXPANDED SAMPLE FROM 0106)
91. BD RETAIL SALES EXCL.CARS-X-12-ARIMA(EXPANDED SAMPLE FROM 0106)
92. BD RETAIL SALES EXCLUDING CARS (
93. BD RETAIL SALES EXCLUDING CARS (EXPANDED SAMPLE FROM 0106) VOLN
94. BD TERMS OF TRADE NADJ
95. BD TERMS OF TRADE - ON THE BASIS OF PRICE INDICESSADJ
96. BD UNEMP.RATE ILO(
97. BD UNEMP.RATE ILO(
98. BD UNEMPLOYMENT LEVEL (PAN BD FROM JAN 1992) VOLA
99. BD UNEMPLOYMENT LEVEL (PAN BD FROM SEPT 1990) VOLN
100. BD UNEMPLOYMENT RATIO AS
101. BD UNEMPLOYMENT:
102. BD UNEMPLOYMENT:
103. BD US $ TO 1 EURO (DEUTSCHEMARK DERIVED HISTORY PRIOR 1999)
104. BD VACANCIES (PAN BD FROM JAN 1994) VOLA
105. BD VACANCIES (PAN BD FROM M0790) VOLN
106. BD VISIBLE TRADE BALANCE CURA
107. BD VISIBLE TRADE BALANCE (PAN BD M0790) CURA
108. BD VISIBLE TRADE BALANCE (TRADE VOLUME ON 2005 BASIS) CONA
109. BD WAGE & SALARY, OVERALL ECONOMY - ON A MTHLY BASIS (
110. BD WAGE & SALARY,OVERALL ECONOMY-ON A MTHLY BASIS(PAN BD M0191)
111. BD WAGES AND SALARIES PER UNIT OF OUTPUT - PROD. SECTOR SADJ
112. BD WPI NADJ
113. BD ZEW INDICATOR OF ECONOMIC SENTIMENT - GERMANY NADJ
114. BD ZEW PRESENT ECONOMIC SITUATION - GERMANY NADJ
115. ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE - U$/BL
116. CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE - U$/TO
117. POLISH ZLOTY TO EURO (WMR) - EXCHANGE RATE
118. POLISH ZLOTY TO 100 JAPANESE YEN(PO) - EXCHANGE RATE
119. POLISH ZLOTY TO UK ? (WMR) - EXCHANGE RATE
120. POLISH ZLOTY TO US $ (GTIS) - EXCHANGE RATE
121. EURO TO UK ? (WMR&DS) - EXCHANGE RATE
122. EURO TO US $ (WMR&DS) - EXCHANGE RATE
123. EURO TO UK ? 1M FWD (WMR) - EXCHANGE RATE
124. EURO TO UK ? 1Y FWD (WMR) - EXCHANGE RATE
125. EURO TO UK ? 1W FWD (WMR) - EXCHANGE RATE
126. EURO TO US $ 1M FWD (BBI) - EXCHANGE RATE
127. EURO TO US $ 1Y FWD (BBI) - EXCHANGE RATE
128. US $ TO JAPANESE YEN (JPM) - EXCHANGE RATE
129. US $ TO HONG KONG $ (GTIS) - EXCHANGE RATE
130. UK ? TO US $ (WMR) - EXCHANGE RATE
131. DAX 30 PERFORMANCE - PRICE INDEX
132. DOW JONES INDUSTRIALS - PRICE INDEX
133. FRANCE CAC 40 - PRICE INDEX
134. FTSE 100 - PRICE INDEX
135. HANG SENG - PRICE INDEX
136. NIKKEI 225 STOCK AVERAGE - PRICE INDEX
137. NASDAQ 100 - PRICE INDEX
138. WARSAW GENERAL INDEX 20 - PRICE INDEX
139. S&P 500 COMPOSITE - PRICE INDEX

.A.6 French Economy - CAC 40

1. FR ANNUAL INFLATION RATE
2. FR AVERAGE COST OF FUNDS FOR BANKS / EURO REPO RATE(MTH.AVG)
3. FR BANKRUPTCIES AT THE BODACC-ALL SECTORS(EXC. AGRICULTURE) VOLN
4. FR BANKS PRIME LENDING RATE
5. FR BOP: CAPITAL AND FINANCIAL ACCOUNT CURN
6. FR CAPITAL MARKET YIELDS-13-WEEK TREASURY BILLS,MO.WGHTD.AVG.
7. FR COLLECTIVE GOVERNMENT CONSUMPTION CURA
8. FR COLLECTIVE GOVERNMENT CONSUMPTION CONA
9. FR COLLECTIVE GOVERNMENT CONSUMPTION CONA
10. FR COLLECTIVE GOVERNMENT CONSUMPTION (
11. FR COLLECTIVE GOVERNMENT CONSUMPTION (
12. FR COMPOSITE LEADING INDICATOR (TREND RESTORED)
13. FR COMPOSITE LEADING INDICATOR (TREND RESTORED) (
14. FR CONSUMER SPENDING CURA
15. FR CONSUMER SPENDING CONA
16. FR CONSUMER SPENDING (
17. FR CONSUMER SPENDING (
18. FR CPI SADJ
19. FR CPI - ALL ITEMS LESS ENERGY NADJ
20. FR CPI - HARMONISED EUROPEAN UNION BASIS (2005=100) NADJ
21. FR CPI (
22. FR CPI (NEW METHODOLOGY FROM JANUARY 1998) NADJ
23. FR CPI (NEW METHODOLOGY FROM JANUARY 1998) (
24. FR CURRENT ACCOUNT - GOODS CURN
25. FR CURRENT ACCOUNT - GOODS, EXPORTS CURN
26. FR CURRENT ACCOUNT - GOODS, IMPORTS CURN
27. FR CURRENT ACCOUNT BALANCE CURA
28. FR EMPLOYMENT VOLA
29. FR EMPLOYMENT (
30. FR EMPLOYMENT GROWTH-TOTAL EXCL.AGRIC,ADMIN, EDUC. & HEALTH SADJ
31. FR EXPORT UNIT VALUE INDEX SADJ
32. FR EXPORTS - GOODS & SERVICES CURA
33. FR EXPORTS - GOODS & SERVICES CONA
34. FR EXPORTS - GOODS & SERVICES CONA
35. FR EXPORTS FOB CURA
36. FR EXPORTS FOB (
37. FR EXPORTS FOB (
38. FR FOREIGN ASSETS NET (MONETARY SURVEY) CURN
39. FR FRENCH FRANC EFFECTIVE EXCH. RATE INDEX(USE EMXTW..NF) NADJ
40. FR FRENCH FRANCS TO US $ (MTH.AVG.)
41. FR GDP CURA
42. FR GDP CONA
43. FR GDP CONA
44. FR GDP - IPD SADJ
45. FR GDP - IPD (
46. FR GDP (
47. FR GDP (
48. FR GFCF CURA
49. FR GFCF CONA
50. FR GFCF CONA
51. FR GOVERNMENT GUARANTEED BOND YIELD (EP)
52. FR GROSS DISPOSABLE INCOME - HOUSEHOLDS & PRIV.UNINC.COS. CURA
53. FR GROSS OPERATING SURPLUS CURA
54. FR HOURLY WAGE RATE FOR MANUAL WORKERS (SHBO) NADJ
55. FR HOUSEHOLD CONSUMPTION CURA
56. FR HOUSEHOLD CONSUMPTION CONA
57. FR HOUSEHOLD CONSUMPTION CONA
58. FR HOUSEHOLD CONSUMPTION - MANUFACTURED GOODS CONA
59. FR HOUSEHOLD SAVINGS RATE SADJ
60. FR HOUSING STARTED VOLN
61. FR ILO UNEMPLOYMENT RATE SADJ
62. FR IMPORT UNIT VALUE INDEX SADJ
63. FR IMPORTS - GOODS & SERVICES CURA
64. FR IMPORTS - GOODS & SERVICES CONA
65. FR IMPORTS - GOODS & SERVICES CONA
66. FR IMPORTS FOB CURA
67. FR IMPORTS FOB (
68. FR IMPORTS FOB (
69. FR INCREASE IN STOCKS(NET PURCHASES PRECIOUS GOODS NOT INCLUDED)
70. FR INCREASE IN STOCKS(NET PURCHASES PRECIOUS GOODS NOT INCLUDED)
71. FR INDUSTRIAL PRODUCTION - MANUFACTURING VOLA
72. FR INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION VOLA
73. FR INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION (
74. FR INDUSTRY BANKRUPTCIES VOLA
75. FR INDUSTRY BANKRUPTCIES VOLN
76. FR INDUSTRY SURVEY: CAPACITY UTILISATION SADJ
77. FR MFI LOANS TO RESIDENT PRIVATE SECTOR CURN
78. FR MONEY SUPPLY - M1 (NATIONAL CONTRIBUTION TO M1) CURN
79. FR MONEY SUPPLY - M1 (NATIONAL CONTRIBUTION TO M1) (
80. FR MONEY SUPPLY - M2 (NATIONAL CONTRIBUTION TO M2) CURN
81. FR MONEY SUPPLY - M2 (NATIONAL CONTRIBUTION TO M2) (
82. FR MONEY SUPPLY - M3 (NATIONAL CONTRIBUTION TO M3) CURN
83. FR MONEY SUPPLY - M3 (NATIONAL CONTRIBUTION TO M3) (
84. FR NET INTERNATIONAL INVESTMENT POSITION
85. FR NEW CAR REGISTRATIONS VOLA
86. FR NEW CAR REGISTRATIONS VOLN
87. FR NEW JOB VACANCIES FULL & PART-TIME REGISTERED DURING MONTH
88. FR NEW ORDERS: INDUSTRY SADJ
89. FR NON PROFIT INSTITUTIONS SERVING HOUSEHOLDS CONSUMPTION CURA
90. FR NON PROFIT INSTITUTIONS SERVING HOUSEHOLDS CONSUMPTION CONA
91. FR NON PROFIT INSTITUTIONS SERVING HOUSEHOLDS CONSUMPTION CONA
92. FR OFFICIAL RESERVES CURN
93. FR OVERALL BUDGET BALANCE(CMLV., MINISTRY OF FINANCE BASIS) CURN
94. FR PIBOR / EURIBOR - 3-MONTH (MTH.AVG.)
95. FR POPULATION: FRANCE VOLN
96. FR PPI NADJ
97. FR PPI (
98. FR PPI: EXCLUDING FOOD AND ENERGY NADJ
99. FR PRODUCTIVITY - GDP PER EMPLOYED PERSON SADJ
100. FR PRODUCTIVITY PRODN. - INDUSTRY EXCLUDING CONSTRUCTION SADJ
101. FR RETAIL SALES INDEX (VALUE) SADJ
102. FR RETAIL SALES INDEX (VOLUME) VOLA
103. FR RETAIL SALES VALUE INDEX (
104. FR RETAIL SALES VALUE INDEX (
105. FR RETAIL SALES VOLUME INDEX (
106. FR RETAIL SALES VOLUME INDEX (
107. FR SAVINGS - HOUSEHOLDS & PRIVATE UNINC. COMPANIES CURA
108. FR SHARE PRICE INDEX - SBF 250 NADJ
109. FR SURVEY - HOUSEHOLD CONFIDENCE INDICATOR SADJ
110. FR SURVEY: GEN.PROSPECTS-PROBABLE TREND IN INDL. PRODUCTION SADJ
111. FR SURVEY: MANUFACTURING - SYNTHETIC BUSINESS INDICATOR SADJ
112. FR TERMS OF TRADE NADJ
113. FR TRADING PROFIT CURA
114. FR UNEMPLOYMENT LEVEL VOLA
115. FR UNIT LABOUR COST INDEX
116. FR UNIT LABOUR COSTS, RELATIVE NORMALIZED SADJ
117. FR US $ TO 1 EURO (FRENCH FRANC DERIVED HISTORY PRIOR 1999)
118. FR VISIBLE TRADE BALANCE FOB-FOB CURA
119. FR VISIBLE TRADE BALANCE FOB-FOB CURN
120. FR WAGE RATE : HOURLY - MANUAL WORKERS (
121. FR WAGE RATE : HOURLY - MANUFACTURING NADJ
122. FR WAGE RATE : HOURLY - MANUFACTURING (
123. POLISH ZLOTY TO EURO (WMR) - EXCHANGE RATE
124. POLISH ZLOTY TO 100 JAPANESE YEN(PO) - EXCHANGE RATE
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144. NIKKEI 225 STOCK AVERAGE - PRICE INDEX
145. NASDAQ 100 - PRICE INDEX
146. WARSAW GENERAL INDEX 20 - PRICE INDEX
147. S&P 500 COMPOSITE - PRICE INDEX

.B Source Code

Listing 1: main.m

```
clear all;
dataread;

tr = 500;
ev = 200;
lag = 200; % how many days of prediction (!!! lag < ev !!! )
 gloutmg = [];
 gloutsg = [];
 epset;       % set parameters of EP
 popxg = [];
 ranset;
 wghts = [];
 popx =cell(1,shs);
 ensom = cell(1,shs);
 ensos = cell(1,shs);
ranset;
 for j = 1 : sdtf - tr - ev - 1
 j
 for i = 1 : shs
      dtfp{i} = dtf{i}( j : j + tr + ev - 1, :);
 end

 if (j < sdtf - tr - ev)
     dtfop = dtfo( lag + j : lag + tr + j - 1, : );
 else
     dtfop = [];
 end
     net = struct();
     netset;

     epset;

    [ensom{ j }, ensos{ j }, popx, r] = predict( dtfp, dtfop, popx, net, gn, r, j );

     wghts = [wghts; markowitz( ensom{ j }, r.ev )];

 end
```

Listing 2: dataread.m

```
clear all;
[type, sheets] = xlsfinfo('alldata.xls');


shs = size(sheets, 2); %number of countries

% read countries
for i = 1 :shs
 [num, txt, raw]  = xlsread('alldata.xls', char(sheets(i)));
  [a,b]=find(isnan(num)>0);
    if (~isempty(a))
        num(a,b(1))=repmat(num(a(1)-1,b(1)), size(b));
    end
 dtf{i} = num;
end
dates = txt(:,1);

num = []; txt = []; raw = [];

% read futures
[num, txt, raw]  = xlsread('fut.xls');
dtfo = num;
sdtf = size(num,1);
```

Listing 3: epset.m

```
% configure evolutionary programming
gn = struct();
gn.grad = 0.000001;
gn.stop = 0.02;
```

```
gn.evmax = 5000;
gn.pop = 100;
% gn.ev = 2500;
gn.max =1;
gn.min = -1;
gn.var = 0.1;
```

Listing 4: netset.m

```
% configure Neural Network

net.hns = 5;                    % number of hidden neurons
net.ins = 6;       % number of inputs
net.nns = net.hns + net.ins;    % number of all the neurons

vl = cumsum( net.ins : net.nns -1 );
net.vl = vl( end );
net.sl = net.vl + net.hns;         % string length
```

Listing 5: predict.m

```
function [ensom, ensos, popx, r ] = predict( dtf, dtfo, popx, net, gn, r, i)

ensom = [];
ensos = [];
for j = 1 : size(dtf,2)

    input = dtf{j}( :, 2 : end );


    %use PCA to reduce dimension
    [ pc, prinout, pcvars ] = princomp( zscore( input ) );
    cs = cumsum( pcvars ./ sum( pcvars ) * 100 );
    pcv = [1:5];

    % extract input as reduced dimension
    int = prinout( 1 : r.tr, 1 : pcv( end ) );
    ine = prinout( r.tr + 1 : r.te, 1 : pcv( end ) );

    % add bias to input
    net.int = [ ones( size( int, 1 ) , 1 )  int ];
    net.ine = [ ones( size( ine, 1) , 1 )  ine ];


        output = dtfo(:, j);
                                              % rescale desired output into range ( -1 ; 1
                                                  )
        [ outs, r.xmin, r.xmax ] = zrange( output );
                                              % desired output
        net.dot = outs( 1 : r.tr );           % training
     % training of the network
        if ( isempty( popx{j} ));
            [ fitpt, popx{ j }, gev ] = gnn( net, gn );
        else
            [ fitpt, popx{ j }, gev ] = gnn( net, gn, popx{ j } );
        end
    % calculate training output from ensemble

    [ ensomtt, enostt ] = ensout( net, popx{ j }, net.int, r.xmin, r.xmax);
    % calculating evaluation output from ensemble
        [ ensomt, ensost ] = ensout( net, popx{ j }, net.ine, r.xmin, r.xmax);
     ensom  = [ensom ensomt];
     ensos = [ensos ensost];

end
```

Listing 6: markowitz.m

```
function RiskyWts = markowitz( ensom, ev )


ensret = tick2ret( ensom );
[ExpReturn, ExpCovariance, NumEffObs] = ewstats( ensret);
numOfAssets = size( ensom, 2 );
```

```
ExpReturn = ExpReturn*250*100;
ExpCovariance = ExpCovariance * 250 *100;
NumPorts = 50;
[PortRiskO, PortReturnO, PortWts] = frontcon(ExpReturn, ExpCovariance, NumPorts, [], [-1.3*
    ones(1,numOfAssets);1.3*ones(1,numOfAssets)]);

RisklessRate = 5;

[slope,I]=max((PortReturnO-RisklessRate)./(PortRiskO));
RiskyRisk=PortRiskO(I);
RiskyReturn = PortReturnO(I);
RiskyWts=PortWts(I,:);
```

Listing 7: gnn.m

```
function [ fitp, po, fe ] = gnn( net, gn, popx )

% net:
%           ins - input size
%           n   - number of hidden neurons
%           ns  - network size

w = net.sl;

p = gn.pop;

% 1. generate a population of solutions

t1 = 1/ sqrt( 2 * w );
t2 = 1/ sqrt( 2 * sqrt ( w ) );
r = gn.max - gn.min;


% 2. generate population
if ( nargin < 3 )
    popx = ( rand( p, w ) * r + gn.min );        % population of arguments
end
% popx(ceil(p/2)+1 : end,:) = ( rand( p - ceil(p/2), w ) * r + gn.min );       % population of
    arguments
popv = rand( p, w ) * gn.var ;               % variance for the population
fe = 0;

% 2. Evaluate population from 1
for i = 1 : p
    fitp( i, 1 ) = nnfit( net, popx( i, : ), net.int, net.dot );
    fe = fe + 1;
end

pbfit=[];
po = [];

% while( fe < gn.ev )
% while( fe < gn.ev)
while(1)
%       disp(fe);
% disp(pbfit);
% disp(fe);
    popxp = popx;
    popvp = popv;

    % 3.
    % a. Mutate the search space points - for all points in population do:
    % pop( 1, i ) = pop( 1, i ) + pop( 2, i) * random number from gaussian
    % normal distribution
    % - deal with out of range results


    for j = 1 : p
        for i = 1 : w
            while( 1 )      % exclude out of range
                popxt = popx( j, i ) + popv( j, i ) * randn();
                if ( popxt > gn.min && popxt < gn.max )
                    popx( j, i ) = popxt;
                    break;
                end
            end

```

```
            %
            %               popxt = popx( j, i ) + popv( j, i ) * randc();
            %               if ( popxt >= gn.max )  popx( j, i ) = gn.max;
            %               end
            %               if ( popxt <= gn.min ) popx( j, i ) = gn.min;
            %               else popx( j, i ) = popxt;
            %               end
        end
    end

    % b. mutate the mutation strenghts
    % pop( 2, i ) = pop( 2, i ) * exp( t1 * global random number + t2 * local random number )
    % t1 = 1/ sqrt( 2 * ilosc zmiennych )
    % t2 = 1/ sqrt( 2 * sqrt( ilosc zmiennych ) )



    for j = 1 : p
        glr = randn( );
        for i = 1 : w
            lor = randn( );
            popv( j, i ) = popv( j, i ) * exp( t1 * glr + t2 * lor );
        end
    end

    % 4. Calculate fitness of offspring
    for i = 1 : p
        %         fito( i, 1 ) =nnfit( popx( i, 1 : vl ), popx( i, vl + 1 : end ), net.in, n );
        fito( i, 1 ) =nnfit( net, popx( i, : ), net.int, net.dot );
        fe = fe + 1;
    end

    % 5. Take best individual from offspirng and parent
    pop = [ popx; popxp ];
    pov = [ popv; popvp ];

    fit = [ fito; fitp ];

    [v, ind] = sort( fit );

    popx =  pop( ind( 1 : p ), : ) ;
    popv =  pov( ind( 1 : p ), : ) ;
    fitp = v( 1 : p );

    pbfit = [pbfit v( 1 ) ];

%      po =  popx( 1 , :) ;


    po = popx;
     if((pbfit(end) < gn.stop ) || ( (fe > gn.evmax)  && ((pbfit(end-1) - pbfit(end)) < gn.grad )) )
         break;

%          if( (pbfit < gn.stop) || ( (fe > gn.evmax) && ((pbfit(end-1) - pbfit(end)) < gn.grad )) ) break;
     end
end
% 7. Go back to 3
```

Listing 8: ensout.m

```
function [ym, ys, ms] = ensout( net, popx, in, xmin, xmax, do )
% ensemble output
    fitpe = [];
    oute = [];
    for i = 1 : size( popx, 1)
       [fitpet, outet] = nnfit( net, popx( i, : ), in );
       oute = [ oute; outet];
    end

    ym = median( oute );
    ev = size( ym, 2 );
    ym = (ym' + 0.5).*(xmax(1:ev)-xmin(1:ev))+xmin(1:ev);

    ys = std( oute );
    ys = (ys' + 0.5).*(xmax(1:ev)-xmin(1:ev))+xmin(1:ev);
```

```
if (nargin == 6)
    ms = mse( ym - do' );
else
    ms = Inf;
end
```

Listing 9: nnfit.m

```
function [ms, y] = nnfit( net, w, in, do )

s = size( in );

e = 0;
y = [];
for i = 1 : s( 1 )
    y = [y  netoutput( w( 1 : net.vl ), in( i, : ), net.hns ) ];
%     e = e + ( y - do( i ) )^2;
end
% y =sqrt(e / s( 1 ) );
if (nargin == 4)
    ms = mse( y - do' );
else
    ms = Inf;
end
```