Project on Implementation of Advanced Methods of Economic Analyses for Prediction of Exchange Rates in Intense Capital, LLC

Bc. Jaromír Špico

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Tomas Bata University in Zlín
Faculty of Management and Economics

Univerzita Tomáše Bati ve Zlíně
Fakulta managementu a ekonomiky
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ZADÁNÍ DIPLOMOVÉ PRÁCE
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Zásady pro vypracování:

Úvod

I. Teoretická část

- **Na základě kritické literární rešerše popište metody a postupy pokročilých metod ekonomických analýz se zaměřením na predikci měnových kurzů.**

II. Praktická část

- **Popište a zhodnoťte současné techniky používané na predikci vývoje kurzu měn ve firmě Intense capital s.r.o.**
- **Proveďte simulaci různých modelů pokročilých metod ekonomických analýz na historických datech vývoje měnových kurzů.**
- **Navrhněte a zhodnoťte projekt predikce měnových kurzů pro firmu Intense capital s.r.o.**

Závěr

Rozsah práce:	**cca 70 stran**
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[1] BERKA, P. Dobývání znalostí z databází. Praha: Academia, 2003. ISBN 80-200-1062-9.
[2] BÍLA, J. Umělá inteligence a neuronové sítě v aplikacích. Praha : ČVUT, 1998. ISBN 80-01-01769-9.
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[5] ZELINKA, I. Umělá inteligence v problémech globální optimalizace. Praha: BEN, 2002. ISBN 80-7300-069-5.

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Ve Zlíně dne 14. března 2008

Pavelková

doc. Dr. Ing. Drahomíra Pavelková
děkan

UNIVERZITA TOMÁŠE BATI VE ZLÍNĚ
Fakulta managementu a ekonomiky

L.S.

Pavelková

doc. Dr. Ing. Drahomíra Pavelková
ředitel ústavu

ROZŠÍŘENÝ ABSTRAKT V ČESKÉM JAZYCE

Diplomová práce s názvem „Návrh implementace pokročilých metod ekonomických analýz pro predikci měnových kurzů ve firmě Intense capital s.r.o." se zabývá možnostmi využití vybraných moderních přístupů ve statistice, ekonometrii a finanční kybernetice pro predikci cenového vývoje na finančním trhu forex pro malou firmu obchodující na tomto trhu.

Teoretická část je rozdělena do tří kapitol. V první sekci je popsán vznik a vývoj trhu zvaného forex až do podoby, v jaké ho známe dnes. Dále se zde popisují účastníci měnového trhu a jejich úlohy a zájmy, ale i vliv na ostatní účastníky trhu a kurz měny. Krátce jsou charakterizovány hlavní instrumenty, se kterými se na trhu obchoduje. Dostupné jsou v této části i nejnovější čísla z přehledu Banky pro mezinárodní platby z prosince 2007 s údaji, které měny se na finančních trzích obchodují nejčastěji. Následuje charakteristika jednotlivých měnových jednotek. V závěru se popisují obecné rizika, které plynou z podstaty obchodování na forexu.

V druhé části teorie jsou uvedeny vybrané přístupy a metody k predikci měnového vývoje z pohledu ekonomie, statistiky a ekonometrie. Fundamentální a makroekonomická analýza pomáhají předpovědět vývoj na základě ekonomických dat, finančních zpráv a prognóz, avšak pro správné načasování investice nejsou vhodné. Zde je vhodnější použít nástroje technické analýzy, popsány jsou MA a RSI. Nechybí zmínka o podstatném vlivu psychologie na aktuální vývoj a dění na trhu, které dokáže ovlivnit konkrétního jedince ale i velké skupiny účastníků. Klasické ekonomické teorie jako parita kupní síly a jiné jsou pouze uvedeny s odkazem na další literaturu, která podrobně rozebírá, proč jsou neúčinné. Pak následuje část, ve které se uvádějí základní statistické přístupy k analýze časových dat, tj. regresní a korelační analýza, ze kterých vycházeli mnohé moderní ekonometrické teorie a metody. Klasickou ekonometrickou metodou je exponenciální vyrovnávání a tzv. ARIMA, autoregresní integrovaný klouzavý průměr, někdy nazývaný Box-Jenkinsova metoda. Novějším přístupem je GARCH, všeobecná autoregresní podmíněná heteroskedasticita.

Třetí část teorie se zabývá neuronovými sítěmi jako moderního přístupu pro predikci a klasifikaci libovolných dat. Tato hlavní složka současné umělé inteligence má široké praktické využití, ekonomické aplikace jsou uvedeny hned v úvodu. V diplomové práci jsou dostupné jenom nutné teoretické základy pro pochopení procesů, na jakých neuronové sítě pracují. Popsán je model neuronu a model vícevrstvé sítě fungující na principu zpětně šířené chyby (back propagation). Důležitý je fakt, že neuronové sítě pracují jako černá

skřínka a učí se z dat bez ohledu na to, jaká jsou. Pak se naučené přístupy používají na modelování budoucích hodnot pro predikci pomocí simulace na vstupu a získání přiměřené odezvy na výstupu. V závěru teorie jsou uvedeny doporučené postupy pro používání neuronových sítí pro predikci.

Analytická a řešící část se rovněž dělí na tři podkapitoly. V prví podkapitole je charakteristika firmy Intense capital s.r.o. na základě výpisu z obchodního rejstříku. Popisuji zde rovněž obchodní platformu SaxoTrader, kterou jsem si i vyzkoušel jako demo účet. Dále jsem uvedl fakty o způsobu obchodování firmy Intense capital na forexu, které jsem získal rozhovorem s obchodníkem o jeho postoji k predikci a obchodování.

V druhé kapitole praktické části, která je bohatá na grafy, tabulky a postupy práce s dostupným softwarem, jsou zpracovány simulace různých modelů a metod pro predikci měnových kurzů. Čtyři z nich se věnují statistice a ekonometrii (regresní analýza, exponenciální vyrovnávání, ARIMA a GARCH), další čtyři se specializují na neuronové sítě s použitím specializovaných programů.

Ve třetí projektové části diplomové práce je návrh implementace získaných poznatků do praxe. To znamená, jak by se dali konkrétně využít jednotlivé metody, jejich dosažené výsledky a který software by byl vhodný k dalšímu použití.

Klíčová slova: predikce, prognózování, měna, kurz měny, finanční trhy, pokročilé metody ekonomických analýz, ARIMA, GARCH, neuronové sítě, Matlab, forex

ABSTRACT IN ENGLISH

The master thesis deals with advanced prediction methods appropriate for exchange rate forecasting on the forex market from the areas of statistics, econometrics and mainly neural networks methods. Several software packages are used for simulation and back testing of results. The aim is to make a project on implementation of these methods for a small firm trading on the forex market.

Keywords: prediction, forecasting, currency, exchange rate, financial markets, advanced methods of economic analyses, ARIMA, GARCH, neural networks, Matlab, forex

ACKNOWLEDGEMENTS

„ Prediction is very difficult, especially about the future. “

Niels Bohr (1885-1962),
Danish physicist

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CONTENTS

INTRODUCTION

Contemporary financial markets are dynamic and mysterious like never before. Classical economic theories seem not to be working well and thus the risks of big losses on the financial markets are immense for all subjects – individuals, governments, and companies. Every reasonable corporation tries to use up-to-day techniques and find out how to be successful and win out over competition.

Fortunately, I had the opportunity last year to hear something interesting about artificial neural networks at our faculty. The course on Friday afternoon was not attended by many students, but sometimes it is worth doing things contrary to the majority. I was sincerely overwhelmed by the potential of neural networks in prediction of financial markets. I asked myself: if there is such new and modern technology, why it is not used in praxis? These are the reasons why I decided to write my master thesis mainly about neural networks and their application on the forex market.

Before starting to write these lines I had already known that although neural networks are the domain of artificial intelligence, currently they are not perfect and ideal. It matters how they are used. So first aim is to learn something about prediction practically, what can be successfully improved and used sometimes in the future. It is never too late to begin to study new bases of an interesting technology.

The second aim is to successfully present my work shortly before leaving school. According to my personal opinion it is better to be slightly original and differ from others. The third aim is to help the company that gives me the opportunity to write master thesis on their benefit.

However, the thesis keeps in touch with the economic and financial mission of the Faculty of Management and Economics in Zlín, because the technology of neural network is applied on forex and also because by presenting this theme anybody can enrich traditional views on market predictability and maybe some day students will be able to successfully trade using artificial intelligence and other up-to-date prediction techniques and software.

I. THEORY

1 FOREIGN EXCHANGE MARKET

Foreign exchange market (forex or FX) generates a competitive economic environment for currency exchange rates. This kind of dynamic financial global market constantly changes from an imaginary stable equilibrium to system instability, and vice versa. When we look at any figure showing a currency pair over a period of time, we see a restless line going up and down quasi-randomly. The line will never stop or move constantly or linearly, so it is difficult to say which way the line will go in the next period. Trying to guess the next move without any information or empirical tools will certainly result in fifty percent probability of failure (or more). It is like throwing a coin or guessing a winning colour of roulette. The essential approach to studying the exchange rate system is to look very properly at foreign exchange market. Therefore I decided to dedicate one chapter to characterise the global environment in which the exchange rate quotation happens.

1.1 History

It is obvious that the history of foreign exchange market is connected with the history of money. Money is a commodity like any other but with one more special privilege – it is generally accepted equivalent of goods. Historical and local monetary systems continuously shifted from a barter system throughout coins and paper currency to what we know today – credit money. I would like to mention some facts about development of monetary system in the 19th and 20th century.

1.1.1 The Bimetallic Standard

Bimetallism or bimetallic standard is a monetary standard where the monetary unit consists of either a certain amount of a metal or a certain amount of another, with the state monetary authority being ready at all times to coin either metal at the legal price. For example, in the United States for the greater part of the 19th century the dollar was defined as consisting either of 22.5 grains of gold or 371 grains of silver (a grain is 0.065 grams). The legal ratio of gold to silver was 1:16.48. This monetary system is very unstable. Due to the fluctuation of the commercial value of the metals, the metal with a commercial value higher than the legal value tends to be used as metal and is withdrawn from circulation as money. Whenever the market price of silver in terms of gold is sufficiently far from the legal ratio, the economy switches to a monometallic standard, using the relatively cheapest metal as money. In the 19th century like today, both metals were actively traded on the so-called bullion markets, where their price changed every day. With the dollar defined in terms of gold or silver, it doesn't make sense to talk of a dollar price of gold, because this price is legally fixed. Instead of it, the ratio of the price of silver to that of gold is important. This ratio has been very stable for the greater part of the 19th century (see Fig. 1.). Then, suddenly, in the 1870's that ratio goes up and up until it reaches 40. The reason is, the bimetallic franc Germinal and all the European currencies that revolved around it did stabilize the market ratio around the legal ratio fixed at 15 for 1. With one country after the other leaving silver for a full gold standard between 1871 and 1900, the demand for gold increased strongly, while tons of silver were freed. [40, 21]

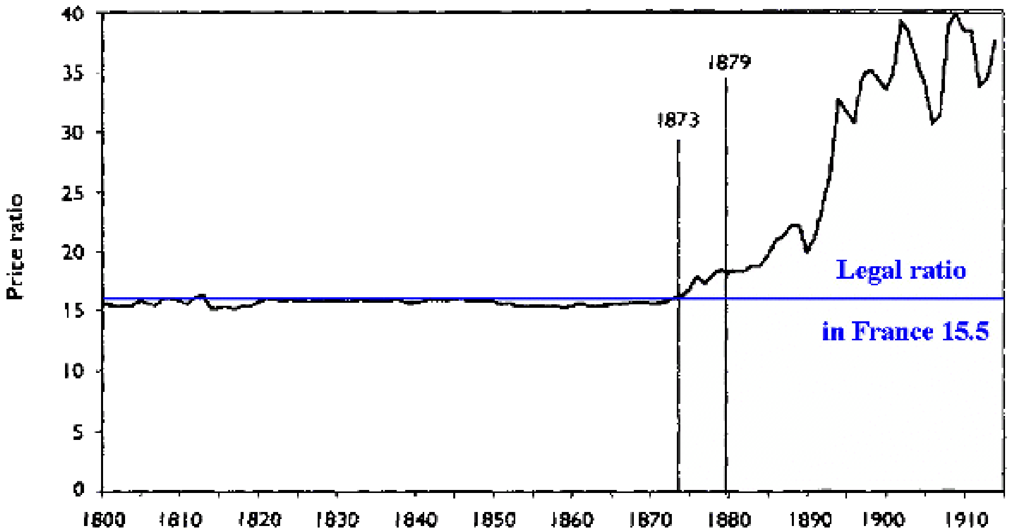


Fig. 1. Ratio of price of gold to price of silver, annually, 1800-1914 [21]

1.1.2 The Latin Monetary Union

In 1865 Italy, France, Switzerland, Belgium and Greece created The Latin Monetary Union. The gold and silver coins of these countries had same weight, diameter and precious metal content and could freely circulate within the other state members just like it is with the Euro from January 1, 2002. After a while many other countries (together 55 countries) started minting their coins following the above standards, although not all of them formally joined the Union: Spain, Austria, Bulgaria, Venezuela, Serbia, and the Papal State.

This bimetallism system created a fixed exchange rate also with countries whose monetary unit was based on different standards but nevertheless bound to gold (gold standard). The exchange rate between different currencies corresponded to the exchange rate of their gold standards. [18, 34]

1.1.3 The Gold Standard

Between 1871 and 1900 every major country except China left their silver or bimetallic standard for a full gold standard. The reason is, after the Franco-German war of 1871, the victorious Germans asked for a very heavy "war indemnity" to be paid in gold by France. They used this gold to finance a new gold standard for their country. The effect was to increase the demand for gold and to unload tons of silver on the neighbouring countries. These countries decided to follow Germany, in fear of silver inflation. That was, at least, the reason invoked to institute a gold standard.

The gold standard system came to an end with World War I. Hence, foreign exchange, as we know it today, really started after this period. Currencies were convertible into either gold or silver, but the main currencies for trading purposes were the British pound and, to a lesser extent, the American dollar. The amounts were relatively small by today’s standards, and the trading centres tended to exist in isolation. [21, 29, 34]

1.1.4 The Bretton Woods System

Convertibility ended with the Great Depression. The major powers left the gold standard and fostered protectionism. As the political climate deteriorated and the world headed for war, the foreign exchange markets all but ceased to exist. In 1944, the post-war system of international monetary exchange was established at Bretton Woods in New Hampshire, USA. The intent was to create a gold-based value of the American dollar and link other major currencies to the dollar. This system allowed for small fluctuation in a 1% band. International institutions such as the IMF, the World Bank and GATT were created in the same period. The US dollar was fixed at 35 $ per ounce of gold and fixed the other main currencies to the dollar - and was intended to be permanent. [27, 29]

1.1.5 Floating and Fixed Exchange Rates

The Bretton Woods system came under increasing pressure as national economies moved in different directions during the sixties. A number of realignments kept the system alive for a long time, but eventually Bretton Woods collapsed in the early seventies following President Nixon's suspension of the gold convertibility in August 1971. The dollar was no longer suitable as the sole international currency at a time when it was under severe pressure from increasing US budget and trade deficits. [27]

Nowadays, there are two ways the price of a currency can be determined against another. A fixed, or pegged, rate is a rate the government (or central bank) sets and maintains as the official exchange rate. A set price is determined against a major world currency (usually the U.S. dollar, but also other major currencies such as the euro, the yen, or a basket of currencies). Unlike the fixed rate, a floating exchange rate is determined by the private market through supply and demand. A floating rate is often termed "self-correcting", as any differences in supply and demand will automatically be corrected in the market. In reality, no currency is wholly fixed or floating. In a fixed regime, market pressures can also influence changes in the exchange rate. A central bank will often then be forced to revalue or devalue the official rate so that the rate is in line with the unofficial one, thereby halting the activity of the black market. In a floating regime, the central bank may also intervene when it is necessary to ensure stability and to avoid inflation; however, it is less often that the central bank of a floating regime will interfere. [12]

1.2 Major Participants

Banks (trading banks) deal with each other in the interbank market, where they are obliged to make a two-way price, i.e. to quote a bid and an offer (a buy and a sell price). This category is perhaps the largest and includes international, commercial and trade banks. These banks rely on the knowledge of the market and their expertise in assessing trends in order to take advantage of them for speculative gain. Other commercial banks have large amounts of foreign exchange business to transact on behalf of their clients. [30]

Corporations are, in the final analysis, the real end users of the foreign exchange market. With the exception only of the central banks that alter liquidity by means of their intervention, it is the corporate player by and large who affects supply and demand. When the other major players enter the market to buy and sell currencies, they do so not because they have a need, but in the hope of a quick and profitable return.

Central banks are the traditional moderators of excess. The Bank of England, the European Central Bank, the Swiss National Bank, the Bank of Japan, the Federal Reserve Bank and other central banks will enter the market to correct what are felt to be unnecessarily large movements, often in conjunction with one another. By their actions, however, they can sometimes create the excesses they are specifically trying to prevent. Monetary authorities occasionally intervene in the foreign exchange market to counter disorderly market conditions. The second group of banks can best be described as aggressive managers of their reserves. Some of the Middle Eastern and Far Eastern central banks fall into this category. They are major speculative risk takers and their activities often disturb market equilibrium. [5]

Investment management firms usually manage the large accounts on behalf of the clients like pension funds and endowments. They use the foreign exchange market to facilitate the trading transactions in terms of foreign securities. For example, an investment manager with an international portfolio for equity will need to purchase and then sell foreign currencies in the spot market so as to pay for the purchases of the foreign equities and since the forex deals comes secondary to the actual decision for investments, they are not seen as a speculative scheme with the aim for maximizing the profit. [9]

Hedge funds, such as George Soros's Quantum fund, have gained a reputation for aggressive currency speculation since 1990. They control billions of dollars of equity and may borrow billions more, and thus may overwhelm intervention by central banks to support almost any currency, if the economic fundamentals are in the hedge funds' favour.

In the **retail forex industry** market makers often have two separate trading desks- one that actually trades foreign exchange (which determines the firm's own net position in the market, serving as both a proprietary trading desk and a means of offsetting client trades on the interbank market) and one used for off-exchange trading with retail customers (called the "dealing desk" or "trading desk"). [10]

1.3 Roles Played

Market makers are those market participants that both buy and sell currencies. As market makers, dealers (or traders) generally, according to market practice, quote a two-way price to another market maker, but not to most corporations. For market makers, reciprocity is standard practice. They constantly make prices to one another. Market makers are primarily major banks, for example, Barclays, Midland, JPMorgan Chase, Morgan Stanley, Deutsche Bank, Union Bank of Switzerland and Citibank.

Price takers are those market participants who seek to either buy or sell currencies. They are usually corporations and fund managers (investors). For price takers, there is no reciprocity inasmuch as they won’t quote prices back to the other market participants.

The major participants in the market play a number of roles depending on their need for foreign exchange and the purpose of their activities:

International banks are market makers and deal with other market participants.

Regional banks deal with market makers to meet their own foreign exchange needs and those of their clients.

Central banks are in the market to handle foreign exchange transactions for their governments, for certain state-owned entities and for other central banks. They also pay or receive currencies not usually held in reserves and stabilise markets through intervention.

Investment banks can be market makers and deal with other market participants.

Corporations are generally price takers and usually enter into a foreign exchange transaction for a specific purpose, such as to convert trade or capital flows or to hedge a currency position.

Brokers are the intermediaries or middlemen in the market, and as such do not take positions on their own behalf. They act as a mechanism for matching deals between market makers. Brokers provide market makers with a bid and/or offer quote left with them by other market makers. Brokers are bound by confidentiality not to reveal the name of one client to another until after the deal is done.

Investors are usually managers of large investment funds and are a major force in moving exchange rates. They may engage in the market for hedging, investment and/or speculation.

Regulatory authorities, while not actually participants in the market, impact the market from time to time. Regulatory authorities include government and international bodies. Most of the market is self-regulated, with guidelines of conduct being established by groups such as the Bank for International Settlements (the BIS) and the International Monetary Fund (IMF). National governments can and do impose controls on foreign exchange by legislation or market intervention through the central banks.

Speculators seek excess profits as a reward for their activities. [29, 30]

1.4 Foreign Exchange Products

1.4.1 Spot

Currency spot trading is the most popular foreign currency instrument around the world. A spot deal consists of a bilateral contract whereby a party delivers a specified amount of a given currency against receipt of a specified amount of another currency from counterparty, based on an agreed exchange rate. A spot transaction is where delivery of the currencies is two business days from the trade date (except the Canadian dollar, which is one day).

The name "spot" does not mean that the currency exchange occurs the same business day the deal is executed. Currency transactions that require same-day delivery are called cash transactions. The two-day spot delivery for currencies was developed long before technological breakthroughs in information processing. This time period was necessary to check out all transactions' details among counterparties.

The spot market is characterized by high liquidity and high volatility. Volatility is the degree to which the price of currency tends to fluctuate within a certain period of time. [9, 30, 38]

1.4.2 Forward

This is a transaction involving the exchange of two currencies at a rate agreed on the date of the contract for value or delivery at some time in the future (more than two business days).

1.4.3 Futures

This is a forward contract for standardized currency amounts and for standard value dates. Buyers and sellers of futures are required to post initial margin or security deposits for each contract and have to pay brokerage commissions.

1.4.4 Swap

Swap is a transaction which involves the actual exchange of two currencies (principle amount only) on a specific date, at a rate agreed at the time of conclusion of the contract (the short leg) and a reverse exchange of the same two currencies at a date further in the future, at a rate agreed at the time of the contract (the long leg).

Currency swap is a contract that commits two counter parties to exchange streams of interest payments in different currencies for an agreed period of time, and to exchange principle amounts in different currencies at a pre-agreed exchange rate at maturity.

1.4.5 Options

An option is a contract between the buyer (holder) of the option and the seller (or writer) of the option. This contract describes the rights of the option holder and the obligations of the option writer. A currency option is a contract, which gives the owner the right, but not the obligation, to buy or sell a currency with another currency at a specific rate during a specific period.

1.4.6 Exchange Traded Fund

This instrument provides traders and investors the opportunity to participate in markets that were previously unavailable. The Euro Currency Trust (symbol FXE) was the first forex-based ETF. Each share of FXE represents 100 Euros, plus accrued interest (the Euros are on deposit, and as such earn interest). That means each share will have a value of 100 x EUR/USD (the quoted rate of US Dollars per Euro). [29, 30, 37]

1.5 Key Currencies

According to Triennial Central Bank Survey made by Bank of International Settlements in December 2007 [4], there are five main currencies traded in the foreign exchange market:

The United States dollar is the world's main currency. All currencies are generally quoted in U.S. dollar terms. The U.S. dollar became the leading currency toward the end of the Second World War and was at the centre of the Bretton Woods Accord, as the other currencies were virtually pegged against it. The introduction of the euro in 1999 reduced the dollar's importance only marginally. The major currencies traded against the U.S. dollar are the euro, Japanese yen, British pound, and Swiss franc.

The euro was designed to become the premier currency in trading by simply being quoted in American terms. Like the U.S. dollar, the euro has a strong international presence stemming from members of the European Monetary Union. The currency remains plagued by unequal growth, high unemployment, and government resistance to structural changes.

The Japanese yen is the third most traded currency in the world; it has a much smaller international presence than the U.S. dollar or the euro. The yen is very liquid around the world, practically around the clock. The natural demand to trade the yen concentrated mostly among the Japanese keiretsu, the economic and financial conglomerates. The yen is much more sensitive to the fortunes of the Nikkei index, the Japanese stock market, and the real estate market.

Until the end of World War II, **the British pound** was the currency of reference. Its nickname, cable, is derived from the telex machine, which was used to trade it in its heyday. The currency is heavily traded against the euro and the U.S. dollar.

The Swiss franc is the only currency of a major European country that belongs neither to the European Monetary Union nor to the G-7 countries. Although the Swiss economy is relatively small, the Swiss franc is one of the four major currencies, closely resembling the strength and quality of the Swiss economy and finance. Switzerland has a very close economic relationship with Germany, and thus to the euro zone. [9, 38]

From BIS survey on foreign exchange market results statistics in Table 1:

Tab. 1. Currency distribution of reported foreign exchange market turnover, percentage shares of average daily turnover in April [4]

	2001	**2004**	**2007**
US dollar	90.3	88.7	86.3
Euro	37.6	36.9	37.0
Yen	22.7	20.2	16.5
Pound sterling	13.2	16.9	15.0
Swiss franc	6.1	6.0	6.8
Australian dollar	4.2	5.9	6.7
Canadian dollar	4.5	4.2	4.2
Swedish krona	2.6	2.3	2.8
Hong Kong dollar	2.3	1.9	2.8
Norwegian krone	1.5	1.4	2.2

Because two currencies are involved in each transaction, the sum of the percentage shares of individual currencies totals 200% instead of 100%. I omitted twelve less important currencies from the bottom of the original table. [4]

1.6 Risks by the Trading on Forex

Exchange rate risk is the effect of the continuous shift in the worldwide market supply and demand balance on an outstanding foreign exchange position. For the period it is outstanding, the position will be subject to all the price changes. The most popular measures to cut losses short and ride profitable positions that losses should be kept within manageable limits are the position limit and the loss limit. By the position limitation a maximum amount of a certain currency a trader is allowed to carry at any single time during the regular trading hours is to be established. The loss limit is a measure designed to avoid unsustainable losses made by traders by means of stop-loss levels setting.

Interest rate risk is pertinent to currency swaps, forward out rights, futures, and options. It refers to the profit and loss generated by both the fluctuations in the forward spreads and by forward amount mismatches and maturity gaps among transactions in the foreign exchange book. An amount mismatch is the difference between the spot and the forward amounts. For an active forward desk the complete elimination of maturity gaps is virtually impossible. However, this may not be a serious problem if the amounts involved in these mismatches are small. To minimize interest rate risk, management sets limits on the total size of mismatches.

Credit risk refers to the possibility that an outstanding currency position may not be repaid as agreed, due to a voluntary or involuntary action by a counter party. In these cases, trading occurs on regulated exchanges, such as the clearinghouse of Chicago.

Country risk refers to the government's interference in the foreign exchange markets and falls under the joint responsibility of the treasurer and the credit department. Outside the major economies, controls on foreign exchange activities are still present and actively implemented. [9, 38]

2 ECONOMIC, STATISTICAL AND ECONOMETRIC APPROACHES TO EXCHANGE RATES PREDICTION

This theoretical part deals with common methods used by traders to predict exchange rates on the forex market.

2.1 Fundamental and Macroeconomic Analysis

In an efficient market, all unexploited profit opportunities will be eliminated. Many financial economists take the efficient market hypothesis one step further in their analysis of financial markets. Not only do they define efficient markets as those in which expectations are rational—that is, equal to optimal forecasts using all available information—but they also add the condition that an efficient market is one in which prices reflect the true fundamental (intrinsic) value of the assets. [22]

The first factor to note about foreign exchange prices is that they are relative and not absolute. They represent in the broadest sense a comparison of economies and all that this entails – for example, unemployment, inflation, wage performance, and budget balance. The extent to which one country performs better than another will be reflected in the relative value of its currency against the others. Forecasting how a currency will move is still an art rather than a science. The fundamental approach relies on the analysis and understanding of several factors. The fundamentalist will go through an analysis of the country's overall economic performance, i.e. domestic economy, as indicated by the gross domestic product. As statistics on the GDP are released on a quarterly basis, monthly data of key economic indicators like industrial production, personal income, industrial output, retail sales, and so on, will be closely monitored for clues to the exchange rate. [30]

2.2 Technical Analysis

Technical analysis is used for the prediction of market movements outgoing from the information obtained from the past. The main instruments of technical analysis are different kinds of charts, which represent currencies price change during a certain time preceding exchange deals, as well as technical indicators. The latter are obtained as a result of the mathematical processing of averaging and other characteristics of price movements. The instruments of technical analysis are universal and applicable to any forex sector, any currency and any time span. [38]

2.2.1 Moving Average

Moving averages are one of the oldest and most popular technical analysis tools. A moving average is the average price at a given time. A "simple" moving average is calculated by adding the prices for the most recent "n" time periods and then dividing by "n". The classic interpretation of a moving average is to use it to observe changes in prices. Investors typically buy when a price rises above its moving average and sell when the price falls below its moving average. [1]

2.2.2 RSI

The Relative Strength Index (RSI) is a technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset. It is calculated using the following formula:

$$\text{RSI} = 100 - \frac{100}{1 + \text{RS}} \tag{1}$$

$$\text{RS} = \frac{\text{Average Gain}}{\text{Average Loss}} \tag{2}$$

$$\text{Average Gain} = \frac{\text{(previous Average Gain) x 13 + current Gain}}{14}, \tag{3}$$

$$\text{First Average Gain} = \frac{\text{Total of Gains during past 14 periods}}{14}$$

$$\text{Average Loss} = \frac{\text{(previous Average Loss) x 13 + current Loss}}{14}, \tag{4}$$

$$\text{First Average Loss} = \frac{\text{Total of Losses during past 14 periods}}{14}$$

Note: Losses are reported as positive values. [32]

The RSI ranges from 0 to 100. An asset is deemed to be overbought once the RSI approaches the 70 level, meaning that it may be getting overvalued and is a good candidate for a pullback. Likewise, if the RSI approaches 30, it is an indication that the asset may be getting oversold and therefore likely to become undervalued. [12]

2.3 The Psychology of the Foreign Exchange Market

Traditional economic models assume that all market participants are fully rational. This means that participants process information using the best known statistical techniques, that they fully understand the structure of the market, and that their decisions are optimally suited to achieving their personal goals. Rationality is especially important in the context of how market participants form expectations, where it implies that their forecasts should not consistently be biased in any direction, that forecasters should learn from their mistakes, and that forecasts should not be amenable to improvement using readily available information. Are market participants rational? In recent years economists have begun to look beyond optimal human behaviour to focus on actual human behaviour in financial markets. Market participants' forecasts violate three critical dimensions of economic rationality: they are biased, they do not incorporate lessons from past mistakes, and they can be improved using readily available information. [24]

The role of the media is to report news and opinion, not to make predictions and forecasts. If the media perform their task well, then they should be reflecting the opinions and views of their readers, or constituents. The more widespread and intense the views and opinions, the more prominently they should be featured. The article may explain why prices have raised so much and in a roundabout way will reflect the conventional wisdom, thereby giving the general public some powerful reasons they too should buy. To the contrarian, the appearance of such stories is not a signal to buy; rather, it is a sign that is time to think about selling. [26]

2.4 Classic Economic Theories about Prediction of Exchange Rates

Main economic theories and methods to prediction of exchange rates are:

- Purchasing Power Parity
- International Fisher effect
- Interest rate parity

- Balance of payments
- Random walk
- Economic Bubble

The task of this thesis is not to prove if these theories successfully work. According to the author of publication “Foreign Exchange risks and their effective management in a firm” [17], the above mentioned theories absolutely cannot predict future prices of exchange rates. The statistical and empirical evidence is provided in the book.

2.5 Mathematical and Statistical Methods

2.5.1 Regression Analysis

Regression analysis is concerned with the study of the dependence of one variable, the dependent variable, on one or more other variables, the explanatory variables, with a view to estimating and/or predicting the (population) mean or average value of the former in terms of the known or fixed (in repeated sampling) values of the latter. [10]

The most elementary type of regression model is the simple linear regression model, which can be expressed by the following equation:

$$y_t = \beta_1 + \beta_2 X_t + u_t \qquad (5)$$

The subscript "t" is used to index the observations of a sample. The total number of observations, also called the sample size, will be denoted by "n". Thus, for a sample of size "n", the subscript "t" runs from 1 to "n". Each observation comprises an observation on a dependent variable, written as y_t for observation "t", and an observation on a single explanatory variable, or independent variable, written as X_t. There are two unknown parameters, β_1 and β_2, and an unobserved error term u_t in this model. [5]

The method of least squares assumes that the best-fit curve of a given type is the curve that has the minimal sum of the deviations squared (least square error) from a given set of data. According to the method of least squares, the best fitting curve has the property that [19]:

$$\sum_{i=1}^{n} \left[y_i - f(x_i) \right]^2 \to \min \qquad (6)$$

2.5.2 Correlation Analysis

Correlation analysis is a statistical technique that evaluates the relationship between two variables; i.e., how closely they match each other in terms of their individual mathematical change. The question addressed is: if one variable (X) moves or changes in a certain direction does the second variable (Y) also move or change in a similar or complementary direction? The amount of correlation between two variables is found by comparing the sum of the products of the deviations of the two distributions with a measure that combines the sum of squared deviations of the X distribution and the Y distribution. The result is a ratio that is a statistical measure called the correlation coefficient and is (by convention) represented by the lower case letter "r" [15]:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X}).(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2.\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \quad (7)$$

If r = 1, then x and y are perfectly positively correlated. The possible values of x and y all lie on a straight line with a positive slope in the (x, y) plane. If r = 0, then x and y are not correlated. They do not have an apparent linear relationship. However, this does not mean that x and y are statistically independent. If r = -1, then x and y are perfectly negatively correlated. The possible values of x and y all lie on a straight line with a negative slope in the (x, y) plane. [13]

2.6 Econometric Methods

2.6.1 Exponential Smoothing

One of the simplest forecasting methods is the exponential smoothing or exponentially weighted moving average (EWMA) method. The EWMA forecast is [3],

$$S_{t+1} = \alpha.y_t + (1 - \alpha).S_t \quad (8)$$

where y_t is the actual value, S_t is the forecasted value, α is the weighting factor, which ranges from 0 to 1 and “t” is the current time period. [2]

Why is it called "exponential"? Let us expand the basic equation by substituting for S_{t-1} in the basic equation. For example, the expanded equation for the smoothed value S_5 is [14]:

$$s_5 = \alpha\left[(1-\alpha)^0 y_{5-1} + (1-\alpha)^1 y_{5-2} + (1-\alpha)^2 y_{5-3}\right] + (1-\alpha)^3 s_2 \quad (9)$$

Exponential smoothing is a kind of a moving average, where the current and immediately preceding ("younger") observations are assigned greater weight than the respective older observations. Simple exponential smoothing accomplishes exactly such weighting, where exponentially smaller weights are assigned to older observations. [31]

An exponential smoothing over an already smoothed time series is called double-exponential smoothing. In some cases, it might be necessary to extend it even to a triple-exponential smoothing. While simple exponential smoothing requires stationary condition, the double-exponential smoothing can capture linear trends, and triple-exponential smoothing can handle almost all other business time series. [2]

Exponential smoothing has proven through the years to be very useful in many forecasting situations. It was first suggested by C.C. Holt in 1957 and was meant to be used for non-seasonal time series showing no trend. [14]

2.6.2 ARIMA

The publication by Box and Jenkins of *Time Series Analysis: Forecasting and Control* ushered in a new generation of forecasting tools. Popularly known as the Box–Jenkins (BJ) method, but technically known as the ARIMA method, the emphasis of these methods is not on constructing single-equation or simultaneous-equation models but on analyzing the probabilistic, or stochastic, properties of economic time series on their own under the philosophy let the data speak for themselves. Unlike the regression models, in which Y_t is explained by 'k' regressor X_1, X_2, X_3, ... , X_k, the BJ-type time series models allow Y_t to be explained by past, or lagged, values of Y itself and stochastic error terms. For this reason, ARIMA models are sometimes called atheoretic models because they are not derived from any economic theory. [10]

Most time series consist of elements that are serially dependent in the sense that one can estimate a coefficient or a set of coefficients that describe consecutive elements of the series from specific, time-lagged (previous) elements. This is called autoregressive process (AR) and it can be summarized in the equation:

$$x_t = \xi + \phi_1.x_{(t-1)} + \phi_2.x_{(t-2)} + \phi_3.x_{(t-3)} + ... + \varepsilon \quad (10)$$

where ξ is a constant (intercept) and ϕ are the autoregressive model parameters. Put in words, each observation is made up of a random error component (random shock, ε) and a linear combination of prior observations.

Independent from the autoregressive process, each element in the series can also be affected by the past error (or random shock) that cannot be accounted for by the autoregressive component. This is called moving average process (MA):

$$x_t = \mu + \varepsilon_t - \theta_1 . \varepsilon_{(t-1)} - \theta_2 . \varepsilon_{(t-2)} - \theta_3 . \varepsilon_{(t-3)} - \ldots \quad (11)$$

where μ is a constant and θ are the moving average model parameters. Put in words, each observation is made up of a random error component (random shock, ε) and a linear combination of prior random shocks. [31]

We know that many economic time series are nonstationary, that is, they are integrated and their statistical properties depend on time. Therefore, if we have to difference a time series d times to make it stationary and then apply the ARMA(p, q) model to it, we say that the original time series is ARIMA(p, d, q), that is, it is an autoregressive integrated moving average time series, where p denotes the number of autoregressive terms, d the number of times the series has to be differenced before it becomes stationary, and q the number of moving average terms. Thus, an ARIMA(2, 1, 2) time series has to be differenced once (d = 1) before it becomes stationary and the (first-differenced) stationary time series can be modelled as an ARMA(2, 2) process, that is, it has two AR and two MA terms. [10]

2.6.3 GARCH

With time-series data, it is not uncommon for least squares residuals to be quite small in absolute value for a number of successive periods of time, then much larger for a while, then smaller again, and so on. This phenomenon of time-varying volatility is often encountered in models for stock returns, foreign exchange rates, and other series that are determined in financial markets. Numerous models for dealing with this phenomenon have been proposed. One very popular approach is based on the concept of autoregressive conditional heteroscedasticity, or ARCH, that was introduced by Engle in 1982. It is worth mentioning that Robert F. Engle won The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2003 "for methods of analyzing economic time series with time-varying volatility (ARCH)". [5, 23]

ARCH modelling has become a growth industry, with all kinds of variations on the original model. One that has become popular is the generalized autoregressive conditional heteroscedasticity (GARCH) model, originally proposed by Bollerslev in 1986. Whenever a time series is said to have GARCH effects, the series is heteroscedastic, meaning that its variances vary with time. If its variances remain constant with time, the series is homoscedastic. You can think of heteroscedasticity as time-varying variance (volatility). Conditional implies a dependence on the observations of the immediate past, and autoregressive describes a feedback mechanism that incorporates past observations into the present. GARCH is a mechanism that includes past variances in the explanation of future variances. [10, 36]

The simplest GARCH model is the GARCH (1, 1) model, which can be written as [10]:

$$\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 \sigma^2_{t-1} \qquad (12)$$

where error term *u* at time *t* and variance σ^2 at time t, $\alpha_0 > 0$, $\alpha 1 \geq 0$ and $\alpha_2 \geq 0$.

GARCH takes into account excess kurtosis (fat tail behaviour) and volatility clustering, two important characteristics of financial time series. Fat tail risk arises when the possibility that an investment will move more than three standard deviations from the mean is greater than what is shown by a normal distribution. [12, 36]

GARCH models can be applied to such diverse fields as:

- Risk management
- Portfolio management and asset allocation
- Option pricing
- Foreign exchange
- The term structure of interest rates [36]

3 NEURAL NETWORKS

3.1 Forecasting Applications of Neural Networks

Forecasting is one of the most important activities that form the basis for strategic, tactical, and operational decisions in all business organizations. Recently, neural networks have emerged as an important tool for business forecasting. There are considerable interests and applications in forecasting using neural networks. Their role in successful planning in finance, marketing, production, personnel, and other functional areas is well established. Increasingly, businesses have recognized the importance of accurate forecasting in effective operations and enhanced competitiveness. [43]

Neural networks can be used for prediction with various levels of success. The advantage of them includes automatic learning of dependencies only from measured data without any need to add further information (such as type of dependency like with the regression). The neural network is trained from the historical data with the hope that it will discover hidden dependencies and that it will be able to use them for predicting into future. In other words, neural network is not represented by an explicitly given model. It is more a black box that is able to learn something from data. [25]

Neural networks models are often referred to as Artificial Neural Networks (ANN) to differentiate them from biological neural networks and also to emphasize that these models have qualities of artificial intelligence. Table 2 shows how neural network model differs from computers and computer programs.

Tab. 2. The differences between PC and NN [42]

Neural network	Computer
Is trained by adjusting of weights, thresholds and structure	Is programmed with instructions (if, then, go to…)
Memory and operating components are placed together	Process and its memory are separated
Parallelism	Sequential character
Tolerate deviations from original information	Do not tolerate deviations
Self-organization during training	Constancy of program

The use of neural networks is really broad and one can apply them e.g. for identification of radar or sonar signals, prediction of behaviour, classification, optimization or filtration. More business applications are listed in Table 3.

Tab. 3. A sample of ANN forecasting application areas (shortened) [43]

Problems	Studies
Accounting earnings, earnings surprises	Callen et al. (1996), Dhar and Chou (2001)
Business cycles and recessions	Qi (2001)
Business failure, bankruptcy, financial health	Mckee and Greenstein (2000)
Consumer expenditures	Church and Curram (1996)
Commodity price, option price	Kohzadi et al. (1996), Yao et al. (2000)
Consumer choice, marketing category, market development, market segments, market share, marketing trends	Agrawal and Schorling (1996), West et al. (1997), Aiken and Bsat (1999), Wang (1999), Jiang et al. (2000), Vellido et al. (1999)
Electricity demand	Elkateb (1998), Darbellay and Slama (2000),
Exchange rate	Zhang (1998), Leung (2000), Nag (2002)
Futures trading	Kaastra and Boyd (1995), Ntungo (1998)
GDP growth, inflation, industrial production	Tkacz (2001), Chen (2001), Tseng et al. (2001)
International airline passenger volume, tourist demand, travel demand	Nam and Schaefer (1995), de Carvalho et al. (1998), Law (2000)
Inventory control	Bansal and Vadhavkar (1998)
Joint venture performance	Hu et al. (1999)
Mutual fund net asset, fund performance	Chiang et al. (1996), Indro et al. (1999)
Ozone concentration and level, environmental prediction, air quality	Prybutok et al. (2000), Ruiz_Surez et al. (1995), Murtagh (2000), Kolehmainen (2001)
Product demand, product sales, retail sales	Ansuj et al. (1996), Luxhoj et al. (1996)
Project escalation, project success	Thieme et al. (2000), Zhang et al. (2003)
Residential construction demand, housing value	Hua (1996), Goh (1998)
Stock return, stock indices and trend, stock risk	Wang and Leu (1996)
Traffic	Doughetry and Cobbett (1997), Kirby (1997)
US treasure bond	Cheng et al. (1996)

3.2 Neuron Model

The building unit of a neural network is a simplified model of what is assumed to be the functional behaviour of an organic neuron. The human brain contains about 10^{11} neurons. For almost all organic neurons one can distinguish anatomically roughly three different parts: a set of incoming fibres (the dendrites), a cell body (the soma) and one outgoing fibre (the axon). The axons divide up into different endings, each of which makes contact with other neurons. A neuron can receive up to 10 000 inputs from other neurons. The bulb-like structures where fibres contact are called synapses. [39]

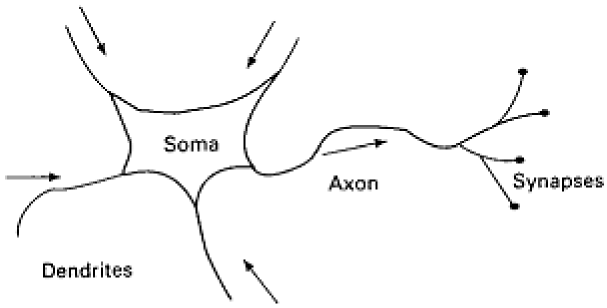


Fig. 2. Simplified biological neuron [39]

An artificial neuron model is shown in Figure 3. The scalar inputs "x" are multiplied by the scalar weights "w" to form "w.x", and then are sent to the summer. A bias "b" is also passed to the summer. The summer output "a", often referred to as the net input, goes into a transfer function "f", which produces the scalar neuron output "y". [11]

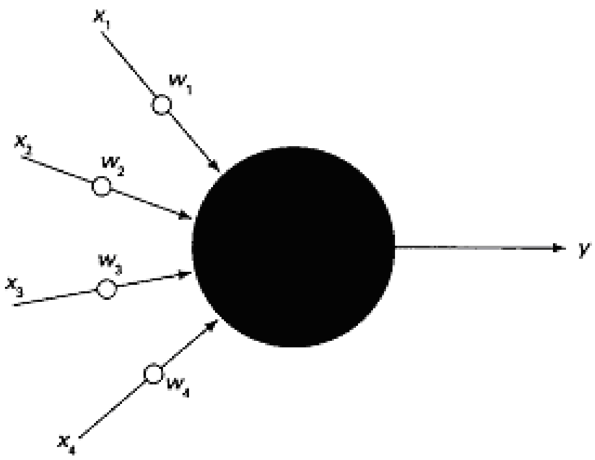


Fig. 3. Artificial model of a neuron [39]

$$a = \sum_{i=1}^{R} w_i . x + b \tag{13}$$

$$y = f(a) \tag{14}$$

The most important transfer function is log-sigmoid. The function logsig has the values in the interval between 0 and 1. The output value could achieve high values in case of not using such type or similar transfer functions. [6, 7]

$$y = \frac{1}{1+e^{-a}} \tag{15}$$

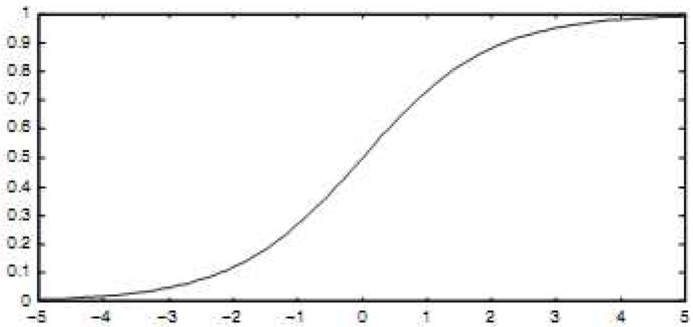


Fig. 4.Log sigmoid function [20]

3.3 Network Architecture

A typical feed forward network has neurons arranged in a distinct layered topology. The input layer serves to introduce the values of the input variables. The hidden and output layer neurons are each connected to all of the units in the preceding layer. Again, it is possible to define networks that are partially-connected to only some units in the preceding layer; however, for most applications fully-connected networks are better. When the network is executed (used), the input variable values are placed in the input units, and then the hidden and output layer units are progressively executed. Each of them calculates its activation value by taking the weighted sum of the outputs of the units in the preceding layer, and subtracting the threshold. The activation value is passed through the activation function to produce the output of the neuron. When the entire network has been executed, the outputs of the output layer act as the output of the entire network. The best-known example of a neural network training algorithm is back propagation. [31]

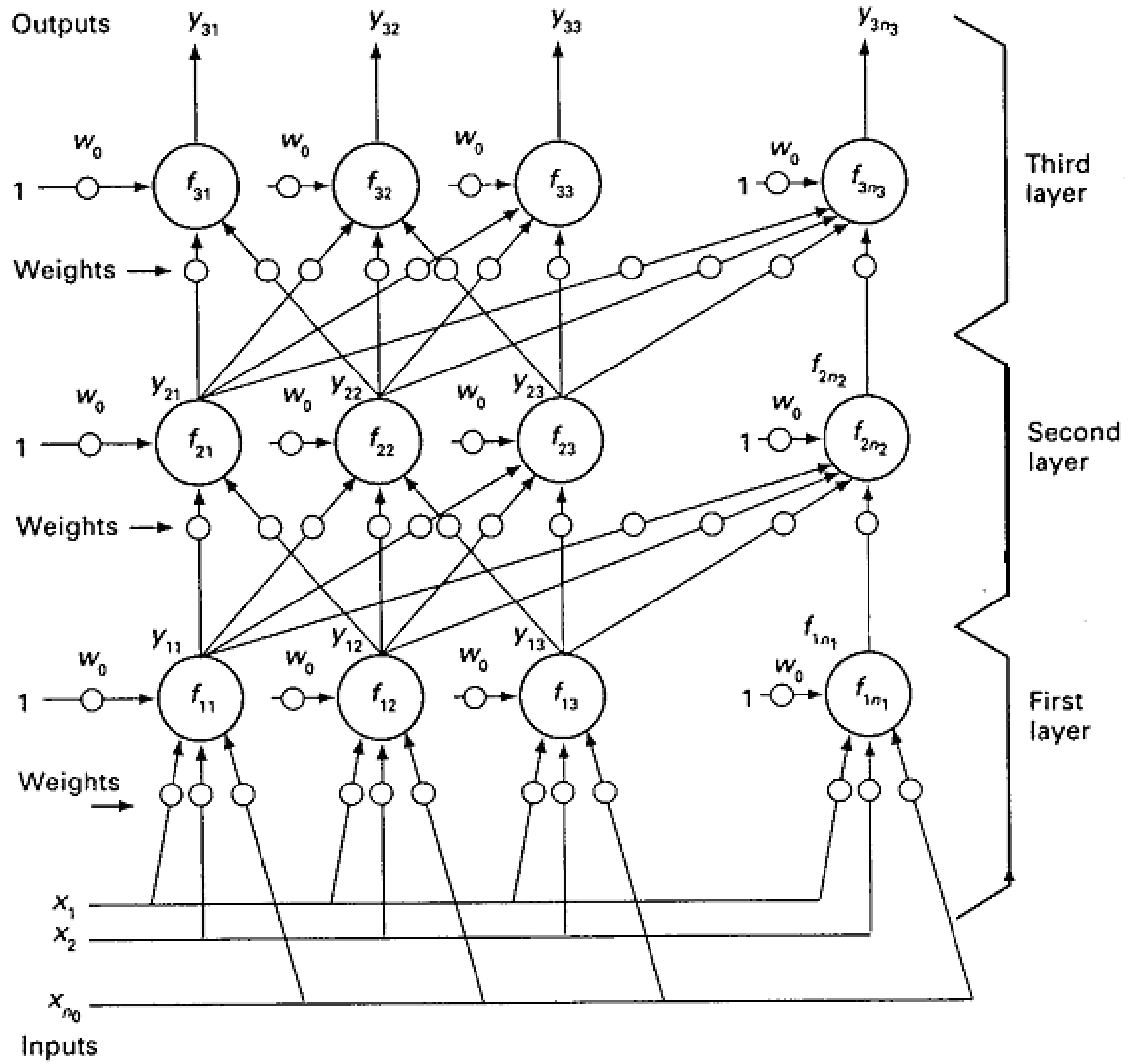


Fig. 5. Structure of multi-layer network with input, hidden and output layer [39]

The back propagation method is used for calculation of weights "w". It consists of two steps. At first it is necessary to make a calculation of outputs on the basis of inputs and weights (forward step). Further the error "E" is calculated as a square difference of calculated output "y" and expected output "o" over all outputs:

$$E = \sum (n_i - o_i)^2 \rightarrow \min \qquad (16)$$

The value of "E" is used for the backward calculation of weights (backward step). The process is repeated till the value of "E" converges to acceptable value. The problem of learning is an optimization task, when the function "E" is fitness function which must be minimized. [6, 7]

3.4 Principles of Prediction with Neural Networks

A great advantage of neural networks is the ability to learn from examples and the ability to catch nonlinear dependencies. A disadvantage is that generally it is impossible to estimate the extent of the error or to determine a confidence interval in advance. The theory of neural networks does not provide any guideline for these problems and therefore the most of these estimations result from heuristic procedures. [33]

The recommended type of network for prediction is multilayer network with back propagation algorithm. Neural network with three layers, which transforms input into output in a simple example of 2 inputs and one output, includes in the first hidden layer 2n+1 neurons and in the next layer n.(2n +1) neurons, that means the topology is for example 2 inputs – 5 neurons – 10 neurons – 1 output value. It was found out empirically that application of Kolmogorovov theorem to neural networks leads to evidence, that for solving of any problem a network of three layers is enough.

If we are talking about prediction, it is a stochastic (it means probable) prediction, because nobody can guarantee that the system will develop in the way we predicted. Whether the system will be predictable or not depends on several criteria, for example if the system is chaotic or deterministic. Another problem is data integrity. If the training data set is not prepared well, results will be useless. Neural networks have an advantage over standard techniques like AR, MA, or ARIMA that there is no need to create models and they are tolerant to signal noises in time series, so reasonable results are obtained

Training data set should consist of input and output vectors with historical data for prediction. Data in training output vector is offset against input by so many time units, how far we want to predict from history into future (for example 3 days ahead). Prediction interval is the length of a section of one output vector. That means the length of prediction for one momentum. If we have as an input the vector of 20 neurons-days and an output is only one neuron-day offset against the last element 3 days ahead, we talk about one day prediction with 3 days advancing. If there are 5 neurons like output, we talk about 5 day prediction with 3 days advancing.

It is obvious from the previous description that there exist a lot of combinations how to predict from the time series. The number of output vectors determines also the offset of vectors between each other. If the first predicted vector is from the dates 1.1.-5.1., the second is from 6.1.-10.1., and so on.

Sometimes differences in training set are used for prediction to avoid trend and seasonal swings. Differences are computed from the last value and the actual value.

The prediction of behaviour on the basis of one historical data is possible, but gives the worst results. Far better results are given when using history of more data about the system. The sample of multiply data prediction is in the Figure 6.

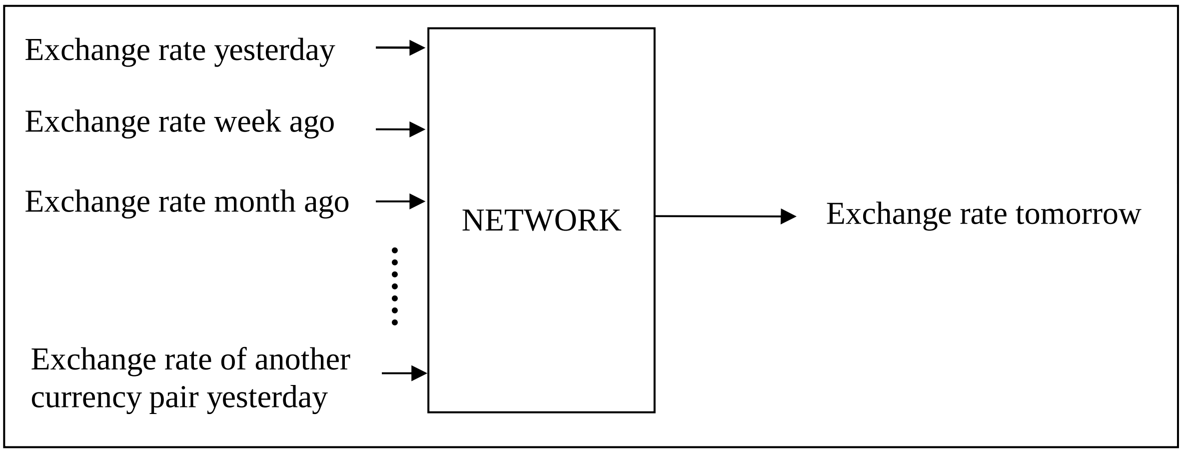


Fig. 6. Multiply prediction [42]

There are two kinds of prediction – classic prediction and auto-prediction. Auto-prediction does not use new observed real input values, but predicted values from our network as new inputs. The next prediction is thus biased by prediction error, which negatively affects the results. It is good not to use auto-prediction for far future.

Secondary prediction technique of exchange rates (except for number values) is using the neural network model for searching for geometrical shapes known from technical analysis. This way the network will be able to identify triangles and other formations. The efficiency can reach 100%, as claimed in publication used in this section. [42]

II. ANALYSIS

4 CONTEMPORARY FOREX PREDICTION IN INTENSE CAPITAL

4.1 Characteristics of the Firm Intense Capital, LLC

Business firm Intense Capital, LLC was founded by Ota Vladař on 21st September 2005. Its registered office is in Zlín, Budovatelská 4810. Legal form of the firm is Limited Liability Company (LLC) and official identification number of the company (IČO) is 27660788. According to the website of the Czech Ministry of Justice <www.justice.cz> the firm's subjects of enterprise are [16]:

- Activity of entrepreneurial, financial, organizational and economic consultants.
- Real estate business activity
- Administration services and services of organizational and business character

Registered capital of the company is 200 000 Czech crowns, all was already paid-up. The firm has only one employee, who is also the statutory body of the firm and owner of the 100% business share. The company‘s website domain is < http://www.intensecapital.cz/ >.

From the above facts is obvious that Intense Capital belongs to young start-up companies, with a small capital and the position of price taker on the forex market.

4.2 Saxo Bank and SaxoTrader Platform

Intense Capital, LLC is a client of Saxo Bank Corporation and uses the trading platform SaxoTrader, version 2. The picture of the platform is available as Appendix A1 at the end of this thesis. Saxo Bank has its headquarters in Denmark and offices in UK, Spain, Singapore, Switzerland, China and Australia and currently employs more than 1,300 employees of 62 different nationalities and serves clients in over 180 countries. Saxo Bank trades more than 150 forex currency crosses and offers accounts from USD 10,000. [28]

The SaxoTrader Platform is a modern trading application offering trading with forex, futures, CFDs and stocks. Everyone can create a demo account and become familiar with trading on financial markets.

The platform used in Intense Capital has the interface in Slovak language, because Czech language is currently not supported. I tried the demo account in English and I liked it very much, because it is stable, well-arranged and rich in information. It provides the user with a lot of useful tools for successful trading, for example instrument explorer, technical analyses indicators, economic calendar, streaming news, UBS and Commonwealth Bank analyses, charts, interest rates etc. The thing I liked most is forex close position tool, which shows the current profit/loss and the trader thus can close position immediately by one click. The A1 appendix of the thesis depicts this tool with the profit USD 100.00 in demo.

The forex spot can be segmented in time units: 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes, and hours (1,2,4,6,8), daily, weekly, monthly and it is also possible to adjust it by trader. The supported kinds of charts are line, dot, line-dot, forest, bar OHLC, bar HLC, candlestick, bid/ask, staircase and comparative. Forex currency pairs are divided into three groups: major (over 100 also with gold and silver in some pairs – reminder of bimetallic standard), minor (35, e.g. EUR/SKK) and exotic (15, e.g. US dollar / Turkish lira).

The previous trading platform used in Intense Capital was Trader Workstation engaged in Interactive Brokers trading account.

4.3 Attitudes towards Trading and Prediction

As I mentioned, Intense Capital is a typical small investor on the forex market, price taker and a speculative day trader. Speculative because the company risks and looks for the market opportunities to profit without any fundamental need to make exchange operations at the defined day or term. Day trading strategy is by contract the sign of conservative attitude to trading, because the trader closes his positions before the end of his day. He never lets the position opened in order to avoid risking a gap the next day morning. The main traded currency pair is EUR/USD and the position is considered to be closed when the capital is kept in USD. The main instruments are spot and futures. Typical investment is 100 000 US dollars and profits are low, but more often than losses. The trader claims that 90% of his trades are profitable. The most popular are Japanese candlesticks in 1 minute sampling. The length of one business trade case varies from 11 seconds (record) to several hours. Stop-loss orders are not used, because the market is watched throughout whole business case. This requires constant attention and is time-consuming therefore the trader invests on forex only 2-5 times monthly. Day trading on forex is not the company’s core business, because there is a lack of employees who could attend to this business constantly.

The approach to prediction is very careful and conservative, too. However, the firm does not use many sophisticated techniques. Fundamental and macroeconomic analyses are performed mainly when trading on the stocks market. The forex market is influenced by unexpected news and expected economic indices from economic calendar. Such news can pretty swing the market up and down. The company's strategy is to avoid trading before and shortly after announcing of globally important economic news. The investor seeks profit, not risk. Maybe this is the reason why the company makes rather small, but more or less sure profits. That also means the trader draws off the market in critical seasons. Fundamental and macroeconomic analyses are therefore performed not purposely, but occasionally by reading economic and financial news and commentaries. When there is a stable positive economic trend or period expected, there is a good chance for trading on the basis of fundamental approach to make small profits rather than going to risk unreasonably. Fundamental and macroeconomic analyses are appropriate for investors, but not for day traders, which is the case of this company.

Fundamental and macroeconomic analyses are connected with psychology of the market and the personality of the trader. Prevailing positive or negative moods can play against the trader's wishes. The trader of Intense Company closes his position when his sixth sense and experience tell him that there is going to be a rush hour. He does not obey "guaranteed" advices from banks and broker news.

Technical analysis indices are applied in a small extent. They serve as an instrument of the right timing. The MA and RSI are utilized classically as it was mentioned in the theory part of the thesis. The trader does not exactly know how RSI is computed.

Classical economic theories like PPP are not considered trustworthy, on the other hand statistical and econometric methods are considered too complicated.

Requirements for a new system of prediction are the simplicity, reliability, low costs and universality. The methods should be able to respond to maximally 10 minutes data and shorter. According to the opinion of the trader from Intense Capital, prediction for more than 10 minutes is useless, because fundamental news with market psychology can suddenly move the position from profit to big losses in a few minutes. The owner of the company is interested in learning to trade with support from new advanced approaches and the results and suggestions will be presented to him in early May 2008.

5 SEARCHING FOR THE BEST FORECASTING METHOD

5.1 Obtaining and Processing Current Forex Market Data

High-quality and valid data are essential for successful prediction. We have to know what is going to be predicted and which variables will be used in models. The answer to this question is not simple. Another point is how the data will be organised, processed and maintained. Although particularly neural networks are data tolerant, we cannot rely on the good luck and random processes. Complete and thorough approach must be implemented and all possible measures must be tested if taking trading with own money seriously. The extent of my thesis and its general sight on numerous methods does not allow trying out all possible models and situations. On the other hand, some of the methods are too complicated to be performed by a non-professional. Thus I will act up to my best effort and common sense when using any of the methods. The second question is how would a trader act during real trading session and what model will be preferred. Especially neural networks offer dozens of possible combinations in different situations.

So, the first obvious question was how to get well prepared and actual data, which could be used not only for back testing, but also for real trading. SaxoTrader trading platform does not offer real time data export, at least according to my knowledge and searching. It only shows data in charts and copying them one by one would be very exhausting. I “googled” a very useful site <http://www.forexrate.co.uk/forexhistoricaldata.php>, still well functioning shortly before finalization of the thesis.

The data are obviously provided by Swiss forex company Dukascopy <http://www.dukascopy.com/> and when I checked the data from Dukascopy and SaxoTrader, I saw no difference. The export format is CSV, which stands for comma separated values. When the file with data is downloaded, in can be simply imported to Excel, Matlab or other programs which allow CSV data import. The user can specify which date will be the last in the data series, how many points he needs (from 250 to 10 000), sampling time interval from 10 seconds to 1 month, the format of the date, the operating system platform (Windows or Unix) and the sign by which the data will be separated (comma, semicolon or tab). Then the user only clicks on the button Get Data and download begins in a few seconds. I used the combination: Data end: today, 10 000 points, 10 minutes interval, d.m.Y date format, windows end line and split by tab. The most important thing is what data we are going to download. In the picture you can see | f | EUR, which stands for EUR/USD currency pair. The next picture shows how data look like in simple text editor.

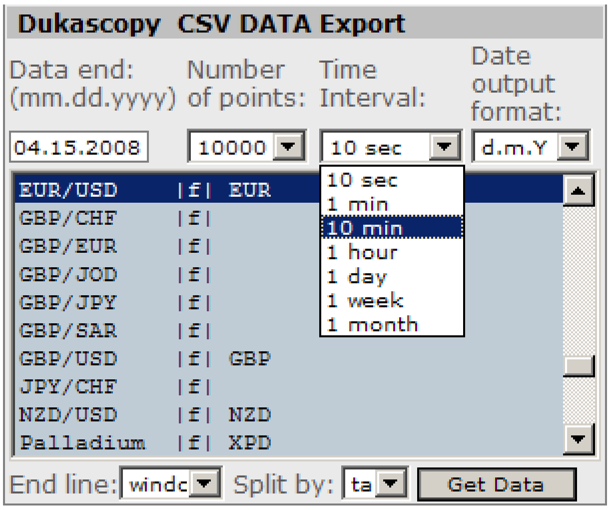


Fig. 7. Real time forex data export

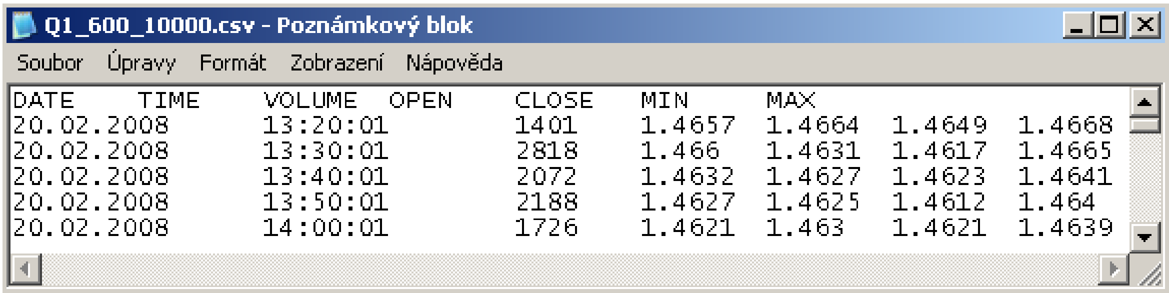


Fig. 8. Inspection of downloaded data

You can see that seven columns are to be imported – date, time, volume, open, close, min and max. These seven variables determine what facts we have about trading for one session, in my case, what is true about trading in ten minutes intervals. I would hardly get any more data, except for calculating myself (moving averages and other technical indicators). So this is what decided the next process of data manipulation.

We have maximally 10 000 values of seven variables concerning time series of EUR/USD in ten minutes sampling. I consequently imported data to Excel through menu Data - Import of external data – Import data… , listed for source and marked the column with date as date format and columns open, close, min and max as text, because Excel would otherwise consider some of these values as dates and imports them incorrectly. When we need to get data to program which needs numbers with comma instead of dot (like Statistica 7), we need to change dots with commas by menu: Edit – Replace – Find “.” and Replace with “,” and Replace all. After then we can copy or import data to data format sensitive software (Statistica collapsed and shut down from numbers with dots).

5.2 Back Testing Method

The data are already reachable and now the question is how we will treat them in models. My suggestion is to use 10 minutes data most often, because it is the requirement of the firm to predict as newest market exchange rates as possible. Shorter time interval will not be used, because development and evaluation of the models takes minimally 10 minutes. But longer time samples are used in order to test the models limitations for longer periods.

Another point is how many data we will use like the base for the models development. Here the situation is strongly individual and depends on the type of model. The minimum case in my thesis is fifty data samples for linear regression up to several thousands samples in case of neural networks. Also the number of columns, that means the number of input variables, depends on model.

The single currency pair that is going to be predicted is EUR/USD and I do not deny that presented models could be more successful, but also more inadequate if they were developed for other currency pairs. The predicted variable is MAX (High), because the firm buys euro for US dollars and then wants to know if euro will be stronger to get back more US dollars from the opposite transactions.

The results will be presented either visually in figures or like comparison of predicted values and actual historical data in numbers or both. The accuracy of the predictions is not the single critical factor for evaluation of the model. It also matters how difficult and time consuming the development of the model is. So I decided also to publish the process of developing the models, not only results. The pictures of software screen dialogues and pieces of source code will be presented step by step when necessary to understand model development from holistic approach. The aim is to make simulations of various methods in available software and help to decide what suggestions could be implemented in the firm and which ones are suitable for employment in practical trading.

5.3 Linear and Polynomial Regression in Microsoft Office Excel 2003

Microsoft Excel is a well-known universal spreadsheet program for common business and administrative needs. It is possible to use it for some simple analyses. Let's mention only the function FORECAST, which does linear regression prediction. The great advantage of Excel tools is their simplicity and availability. The disadvantages are inaccuracies and narrow use for statistical research.

According to my opinion, the best use of Excel for prediction is regression in charts. They show the chosen trend function line, equation of this regression trend, reliability indicator R^2 (between 0 and 1, the higher is better) and are able to predict a few steps ahead.

Therefore I tested linear, polynomial and logarithmic trend functions to show the limits of linear and polynomial regression on the forex market. In figures, the blue line shows real known data before prediction and pink colour unknown real data after prediction. A black line is the prediction by trend function. The prediction is based on time (x) and the predicted value is maximal value of EUR/USD exchange rate in the specified time unit (sometimes called High in the OHLC notation).

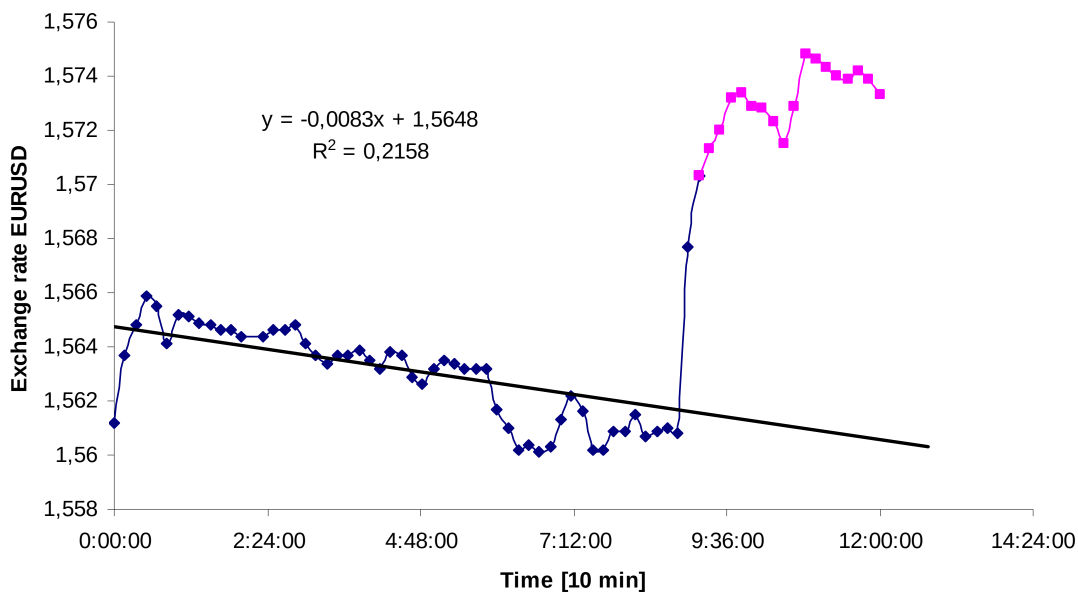


Fig. 9. Simple linear regression

Power and exponential functions were omitted because they are similar to linear and logarithmic functions in the terms of success in predicting this sample data.

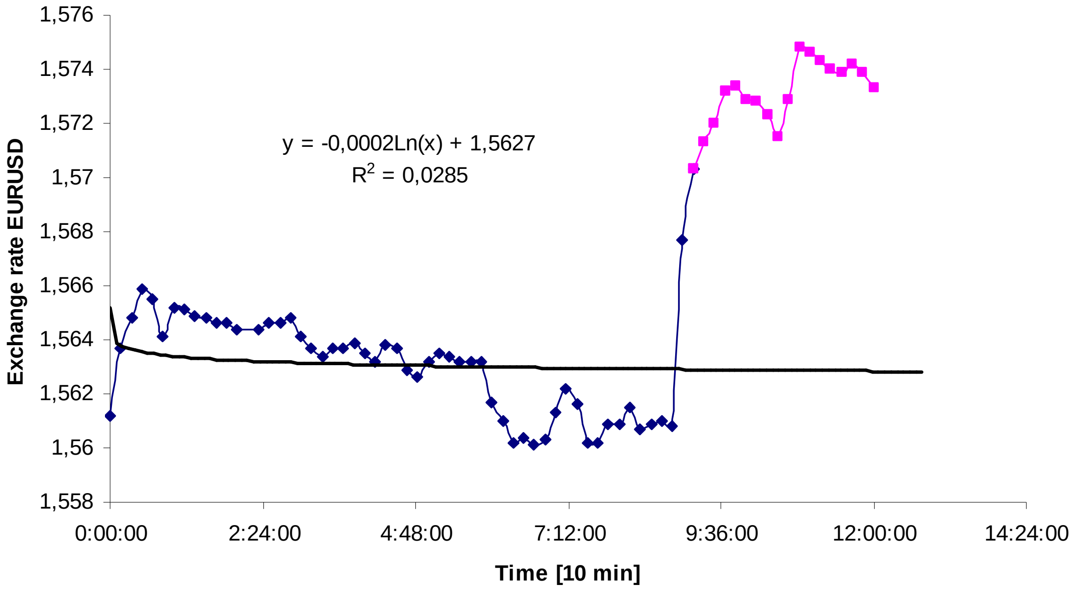


Fig. 10. Logarithmic regression

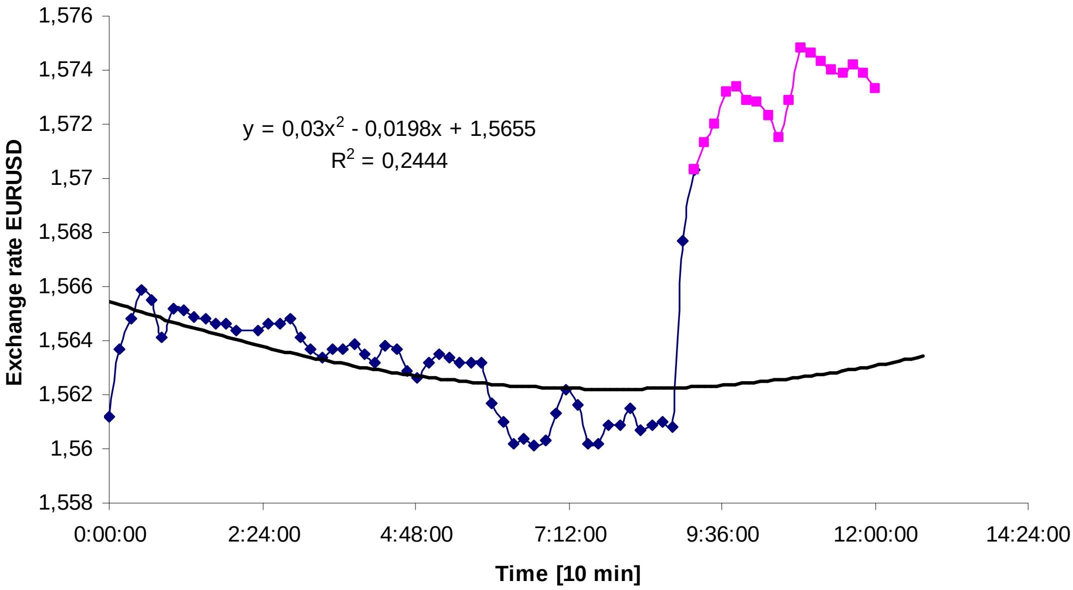


Fig. 11. Polynomial regression – 2nd degree

Polynomial regression of one independent and one dependent variable is the best what can Excel offer. Reliability indicator tends to value of 0,9999 when processing static data from simple time series. This is not the case of forex market data, when it ranges between 0,2 and 0,9, which is not enough for qualified prediction. The equation has the advantage that we can calculate estimation of value at any time just by putting the X values to this equation. The format of equation is important, because its numbers are often rounded, but it is possible to view maximally 15 decimal places after the point, by simple adjusting the format of decimal places in equation.

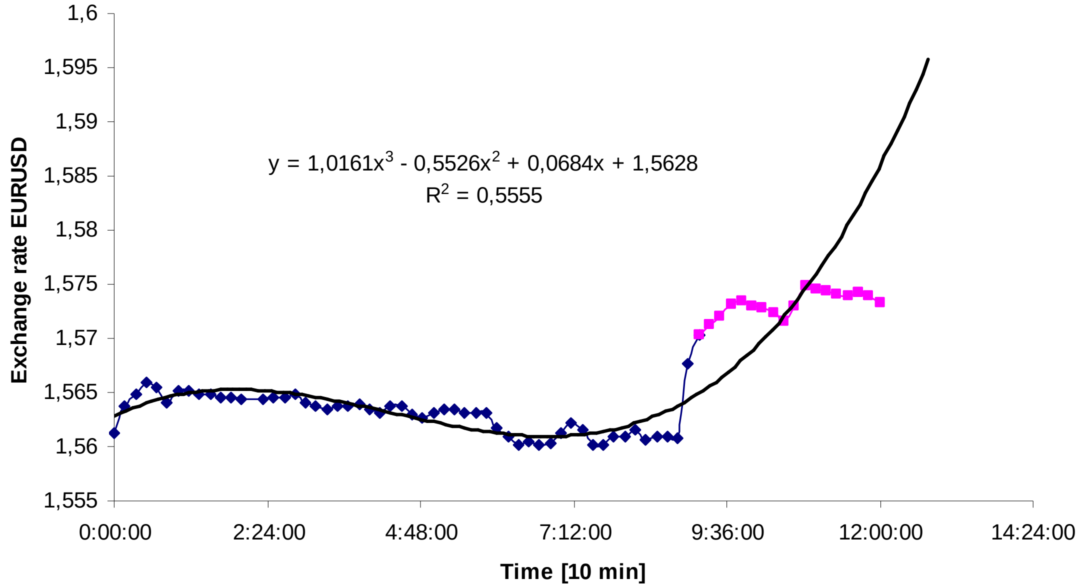


Fig. 12. Polynomial regression – 3rd degree

With the raising polynomial degree the effectiveness apparently gets better, but again – I had to omit the fifth and sixth polynomial degrees because of inaccuracies.

Then I changed the data period from ten minutes to one hour and one day forex data. Maybe the regression could be useful for long run prediction.

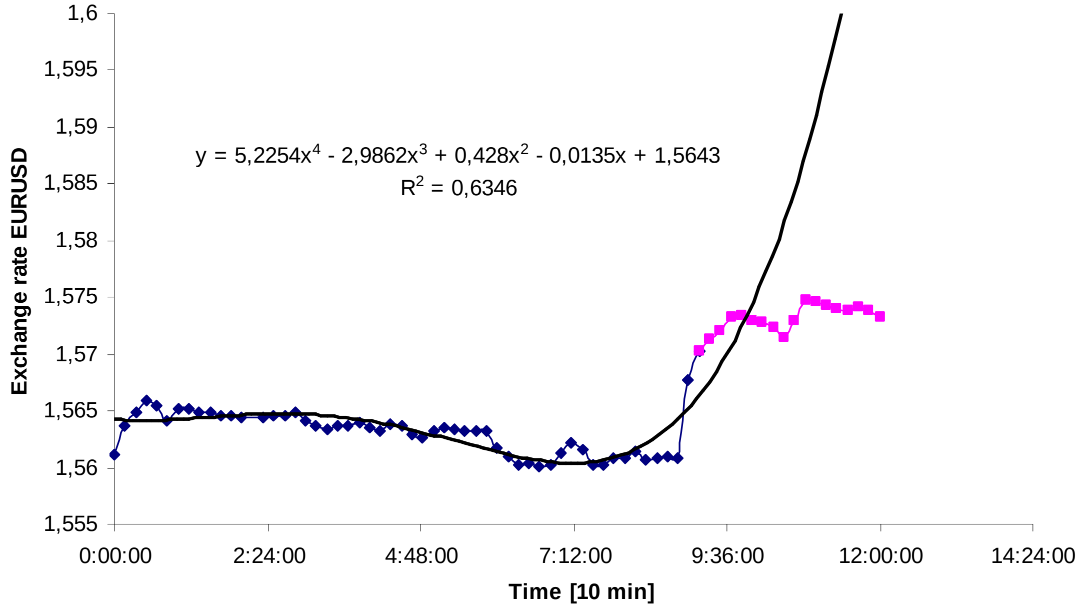


Fig. 13. Polynomial regression – 4th degree

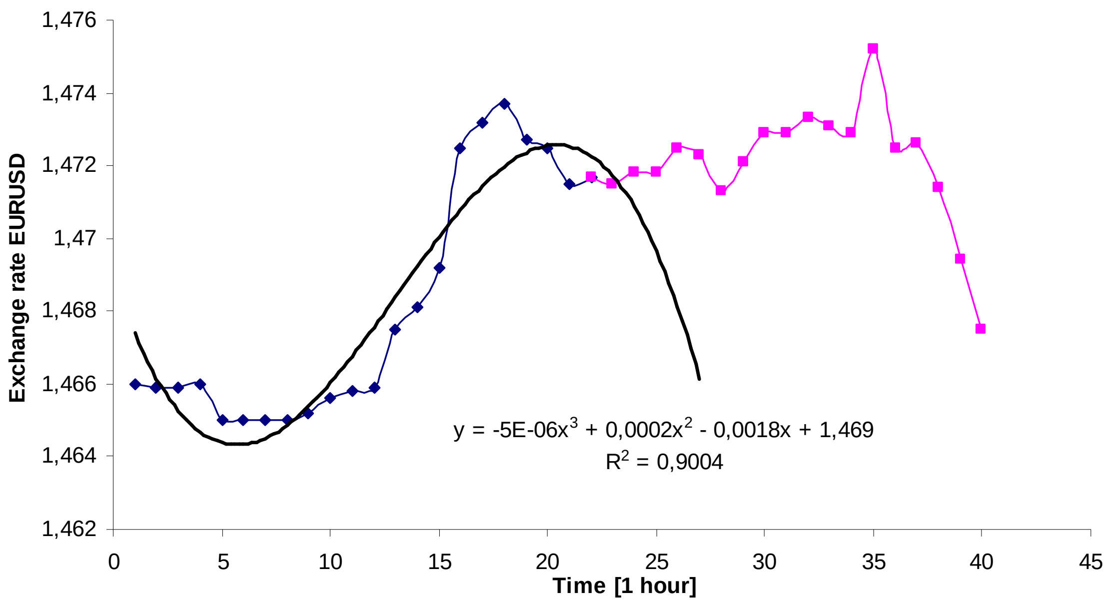


Fig. 14. Polynomial regression – 3rd degree and 1 hour data

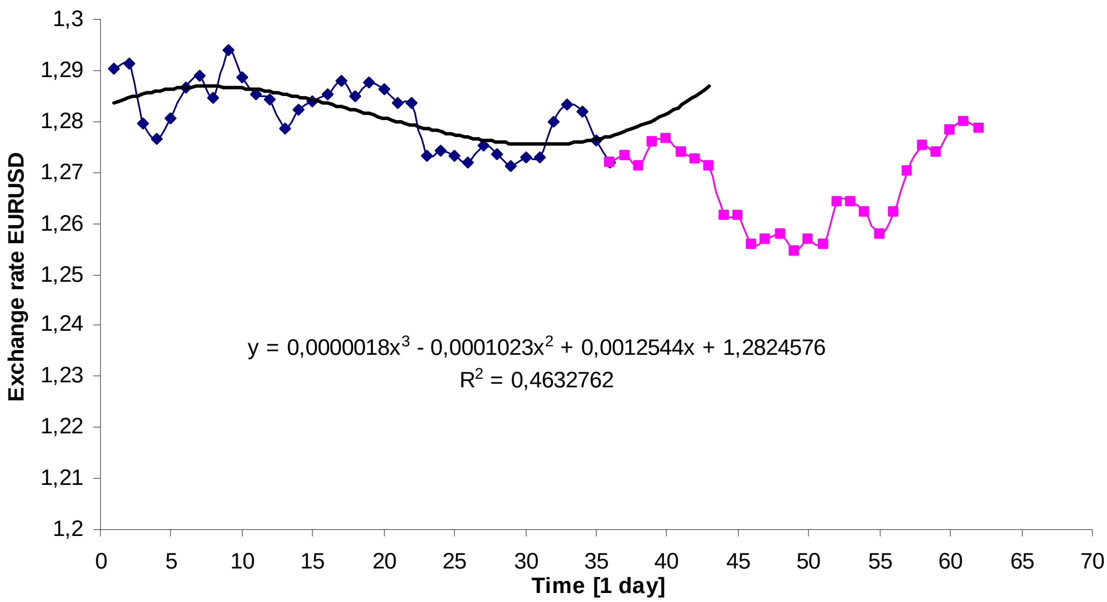


Fig. 15. Polynomial regression – 3rd degree and 1 day data

The 3rd degree polynomial function seems to be the best fitting tool from offered. However, the results are strongly biased and it can not be used for prediction. I would recommend using Excel as first tool after data import to view how the market volatility changes in time and if the trend is strong by viewing its R^2 coefficient.

5.4 Exponential Smoothing, regression and correlation in WinQSB

5.4.1 Time Series Forecasting Tool

The second available software is WinQSB. It is free of charge and offers many subprograms. One of these is Forecasting and Linear Regression. At first I used the part Times Series Forecasting for exponential smoothing prediction method.

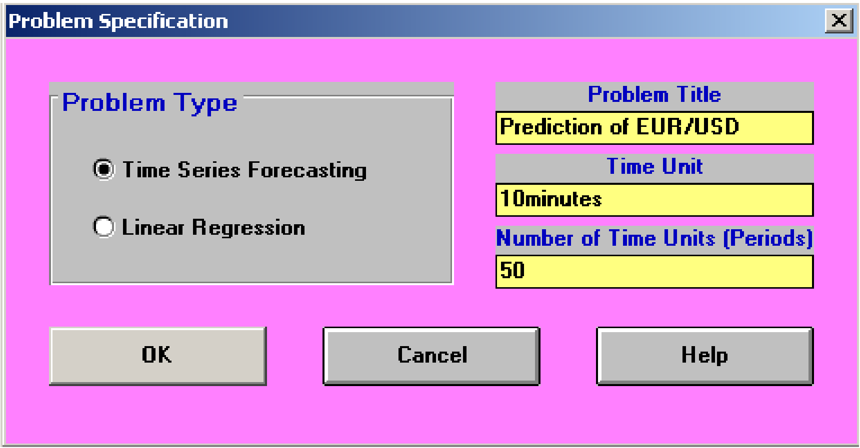


Fig. 16 Dialog for a new problem specification - WinQSB

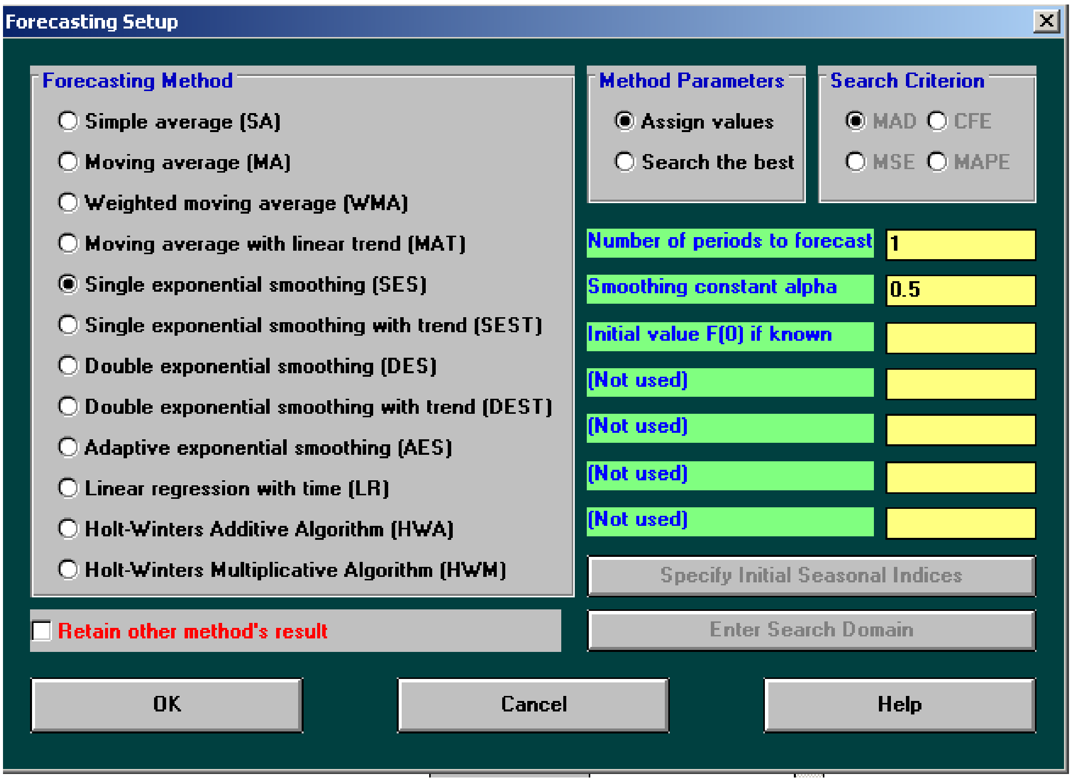


Fig. 17. Several forecasting methods in WinQSB

Unfortunately, WinQSB is not good at work with graphs, so I have to present results as they are. The black lines are the actual data; the blue lines are exponentially smoothed data.

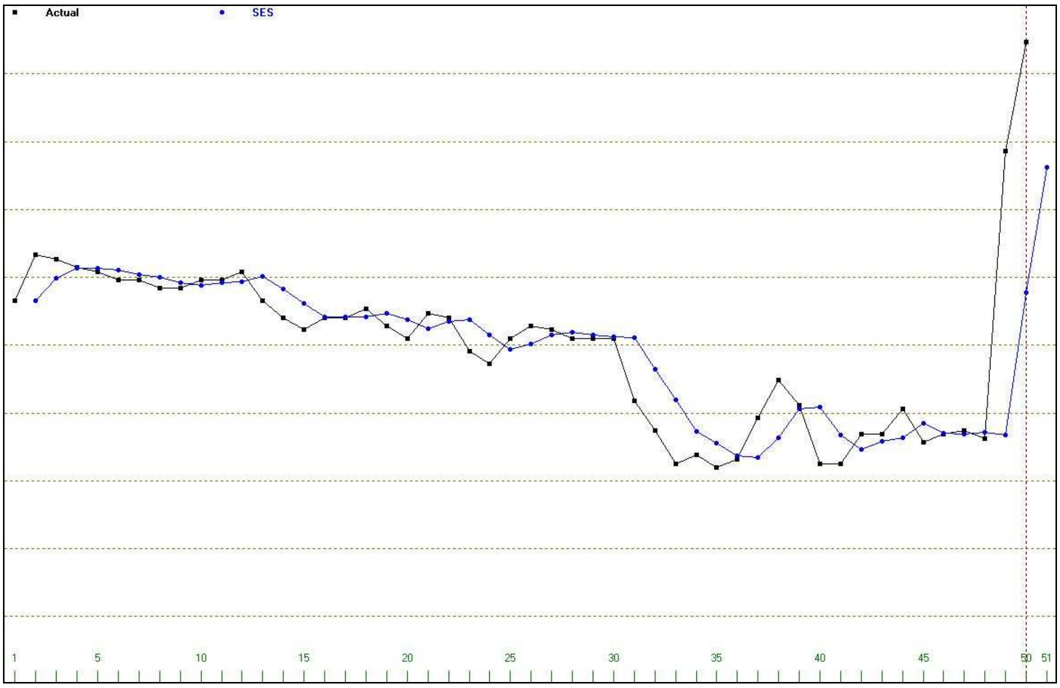


Fig. 18. Simple exponential smoothing - 10 minutes data predicted, 1.5673 is prediction of the actual value 1.5713, alpha factor = 0.5

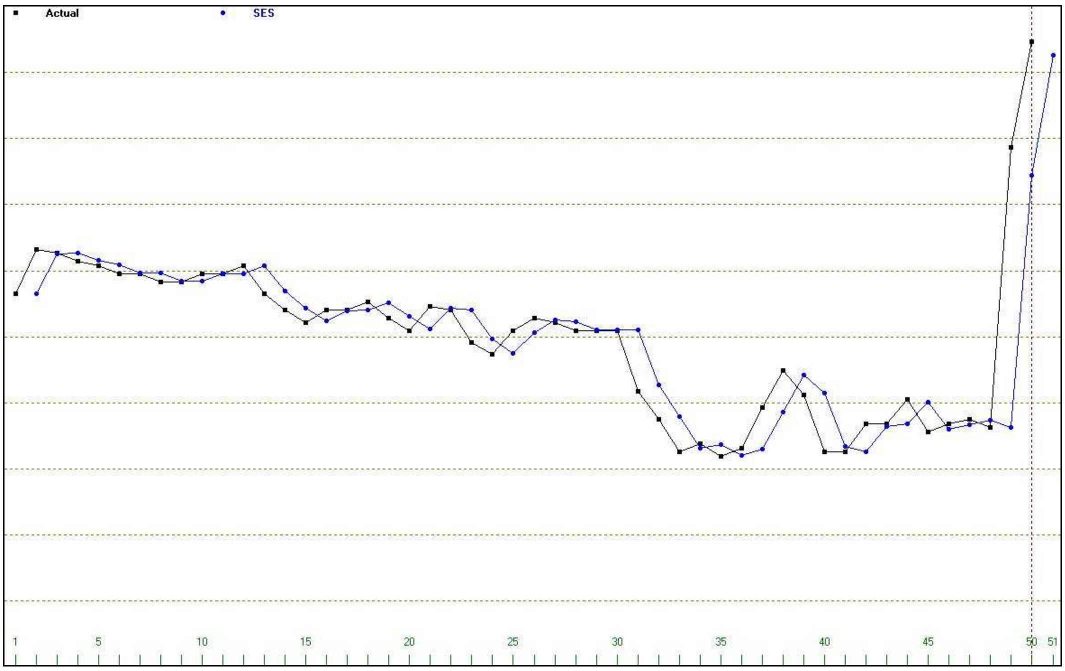


Fig. 19. Simple exponential smoothing - 10 minutes data predicted, 1.5699 is prediction of the actual value 1.5713, alpha factor = 0.9

It would be worth trying all supported prediction methods in WinQSB, but it is not the aim of this thesis. Some of them also need minimal theoretical background, because a lot of parameters have to be estimated empirically. Alpha factor in single exponential smoothing ranges from 0 to 1 and it seems that the higher alpha selected, the more accurate prediction we get at output. Thus the newest values have the greater weight in model when alpha tends to 1. Ten minutes data with 50 historical records were used in the model.

5.4.2 Multiple Linear Regression

WinQSB is able to perform also multifactor regression, that means the predicted value is maximum (or High in OHLC model) of the currency pair EUR/USD and independent factors are Volume, Open, Low, Close and Time.

The historical data were pre-processed in the way that the five independent variables and dependent variable were offset by one time unit, which means they can predict the next step MAX (not the actual one in the session, which is irrelevant). This can be performed in Excel by shifting one column with MAX backwardly and then the data are copied to WinQSB spreadsheet. After solving the problem we get a linear equation similar to the one from Excel, but with 5 input variables instead on one. Then we can compute the prediction in Excel on the basis of this equation, but only one step ahead, because the offset is one. If the offset was e.g. 3 periods, we could compute the prediction of the third value ahead, but not the previous and following values of MAX. For this purpose a new model from data should be derived with the offset to the needed prediction point.

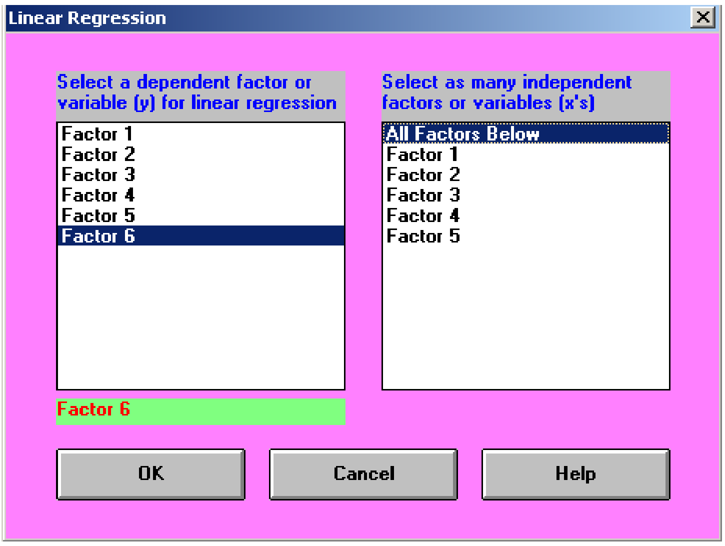


Fig. 20. Linear regression with 6 factors

04-30-2008 06:00:27	Variable Name	Mean	Standard Deviation	Regression Coefficient	Standard Error	t value	p-value
Dependent	Factor 6	1,568219	5,78462E-03				
Y-intercept	Constant			2,275659E-02	7,754076E-02	0,2934791	0,7698066
1	Factor 1	0,351331	0,2049223	1,126095E-04	1,42122E-03	7,923435E-02	0,9370271
2	Factor 2	1673,23	703,8072	8,554812E-07	2,768143E-07	3,090452	2,62928E-03
3	Factor 3	1,567044	5,631971E-03	0,4726838	0,3680401	1,284327	0,2021836
4	Factor 4	1,567208	5,688582E-03	1,297941	0,2277694	5,698489	1,192093E-07
5	Factor 5	1,566229	5,647798E-03	-0,7851602	0,4891934	-1,60501	0,1118462
	Se =	1,566992E-03	R-square =	0,9409194	R-adjusted =	0,9377768	

Fig. 21. The statistical results of multifactor regression

Dependent Variable	Independent Variable
Factor 6 =	2,275659E-02 + 1,126095E-04 Factor 1 + 8,554812E-07 Factor 2 + 0,4726838 Factor 3 + 1,297941 Factor 4 - 0,7851602 Factor 5

Fig. 22. The equation of 6 factor linear regression

04-30-2008	Variable	Variable	Correlation
1	Factor 1	Factor 2	0,5886818
2	Factor 1	Factor 3	0,8015688
3	Factor 1	Factor 4	0,8050804
4	Factor 1	Factor 5	0,7912034
5	Factor 1	Factor 6	0,8069854
6	Factor 2	Factor 3	0,4582084
7	Factor 2	Factor 4	0,5039405
8	Factor 2	Factor 5	0,4379297
9	Factor 2	Factor 6	0,5430076
10	Factor 3	Factor 4	0,9877574
11	Factor 3	Factor 5	0,9908517
12	Factor 3	Factor 6	0,9632822
13	Factor 4	Factor 5	1,007962
14	Factor 4	Factor 6	0,9887459
15	Factor 5	Factor 6	0,9473187

Fig. 23. Correlations between factors

The figure of the factors development cannot be displayed, because there are more than 2 variables in the model and we can see maximally 3D graphs. Charts are available in WinQSB like single variable x and single variable y to show dependencies. But we can easily calculate prediction. This method is thus only numerical. The predicted one step value was 1,5791 and the historical real value was 1,5784. The prediction in WinQSB was derived from 100 historical 10 minutes data.

5.5 ARIMA with Statistica 7

Statsoft Statistica is maybe the world's most popular statistical program. In this part I will show how I performed prediction model ARIMA (1,1,1).

The menu in program is Statistics – Advanced linear/Nonlinear models – Time Series/Forecasting. The data must already be in the spreadsheet. Again, one hundred of 10 minutes data were used, but the columns were not shifted. There were 5 dependent and one independent variable, too. The format of time was edited in Excel from time to number in order to get numbers which can be calculated. For example, the time in format 17:00:01 shifted to 0,708344907407407.

In the dialog variables are selected – again it is the dependency of high EUR/USD currency values. We select the depended variable by locking it in the selection Variables. Then we select the button ARIMA & autocorrelations functions and in the next dialogue the parameters of the model are chosen. I used one very popular combination – p=1, d=1 and q=1.

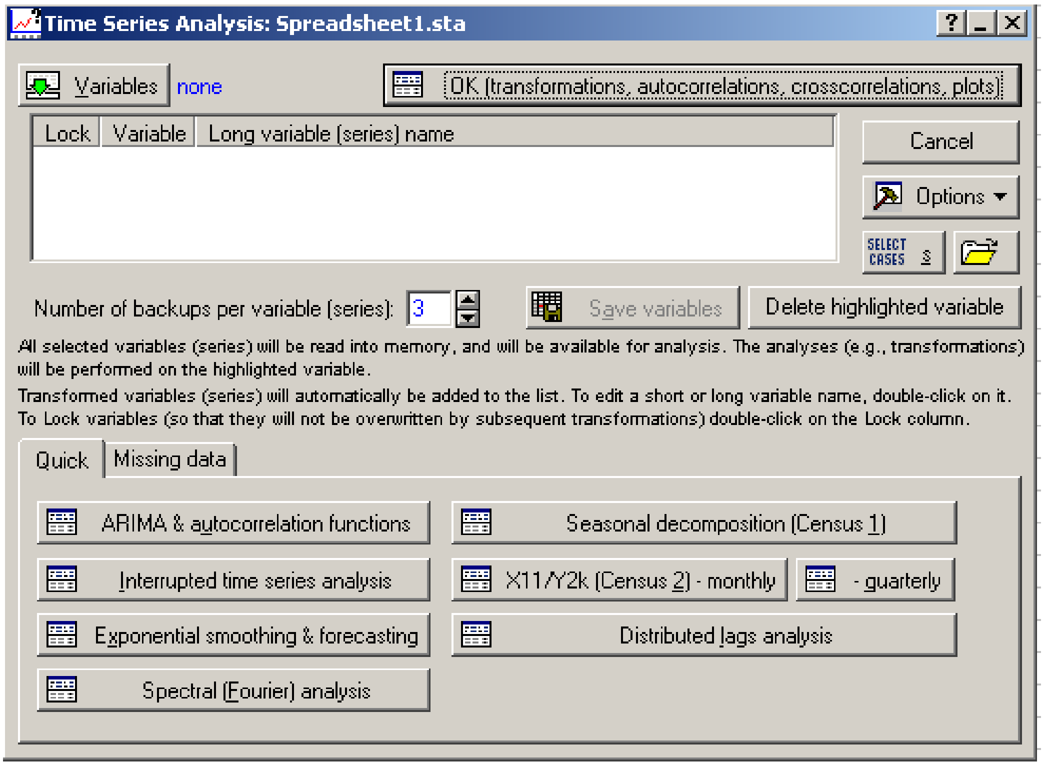


Fig. 24. Time Series/Forecasting in Statistica

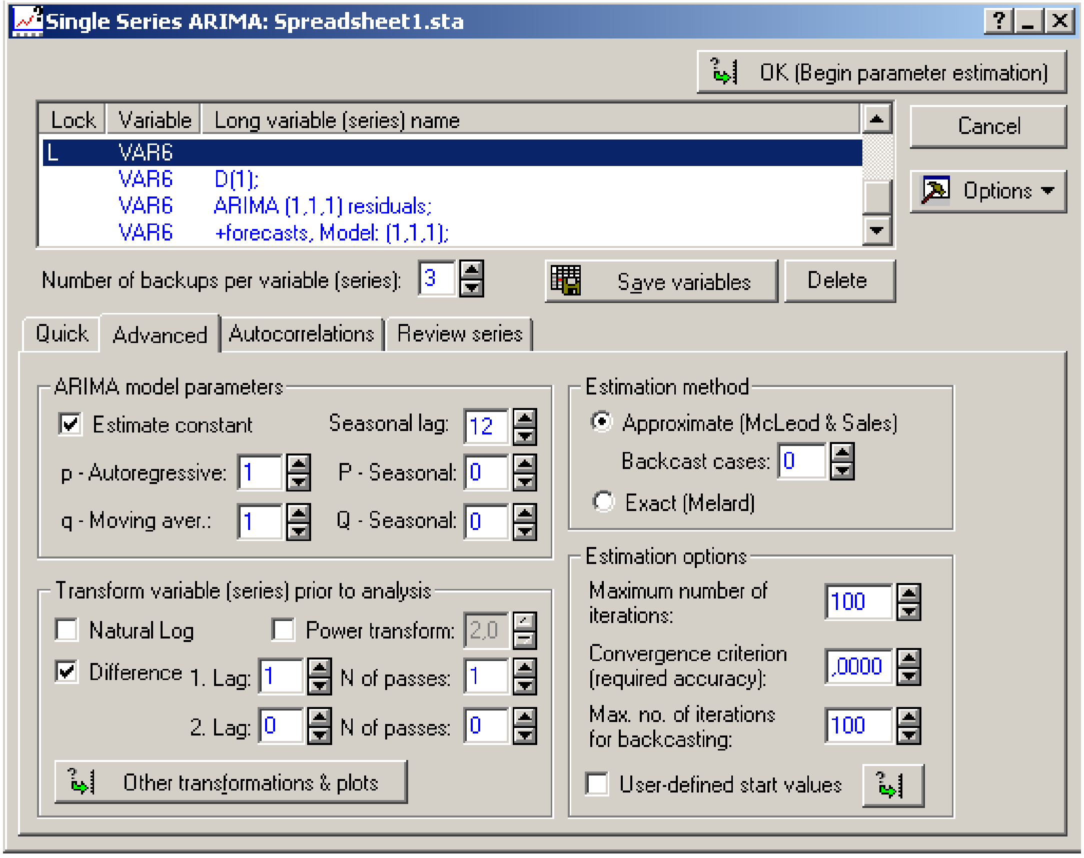


Fig. 25. ARIMA model paramaters

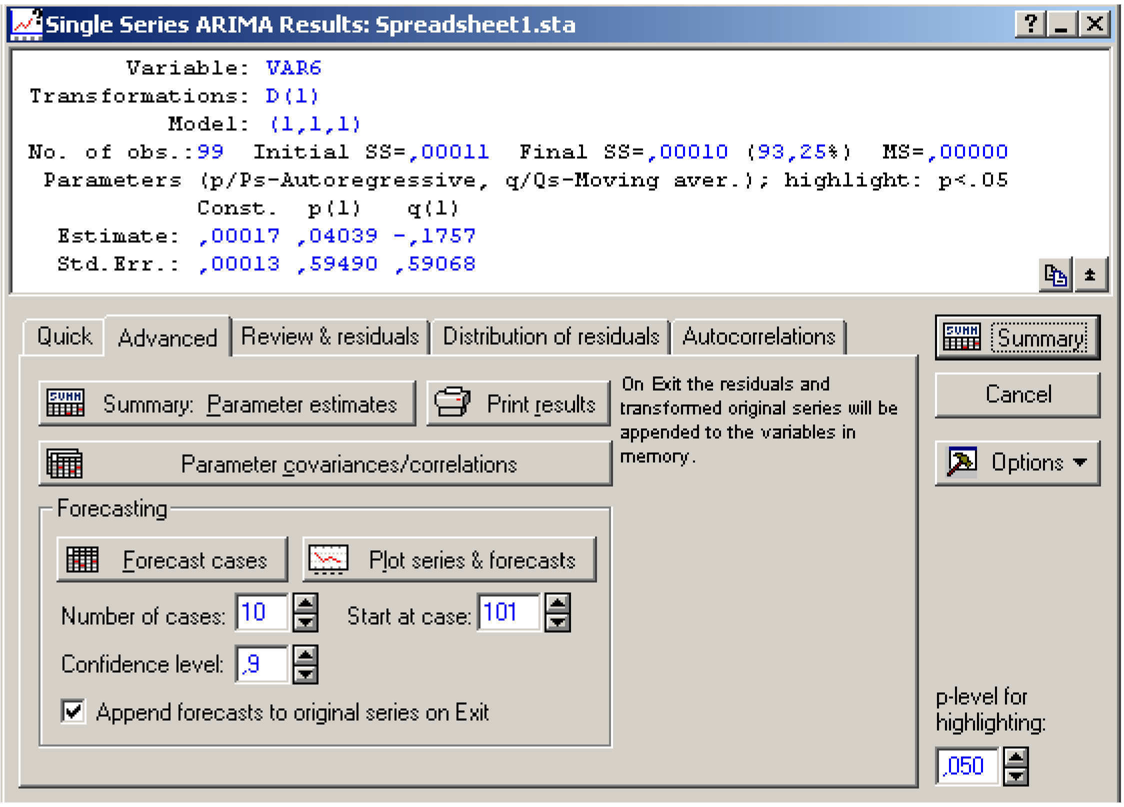


Fig. 26. ARIMA (1,1,1) results

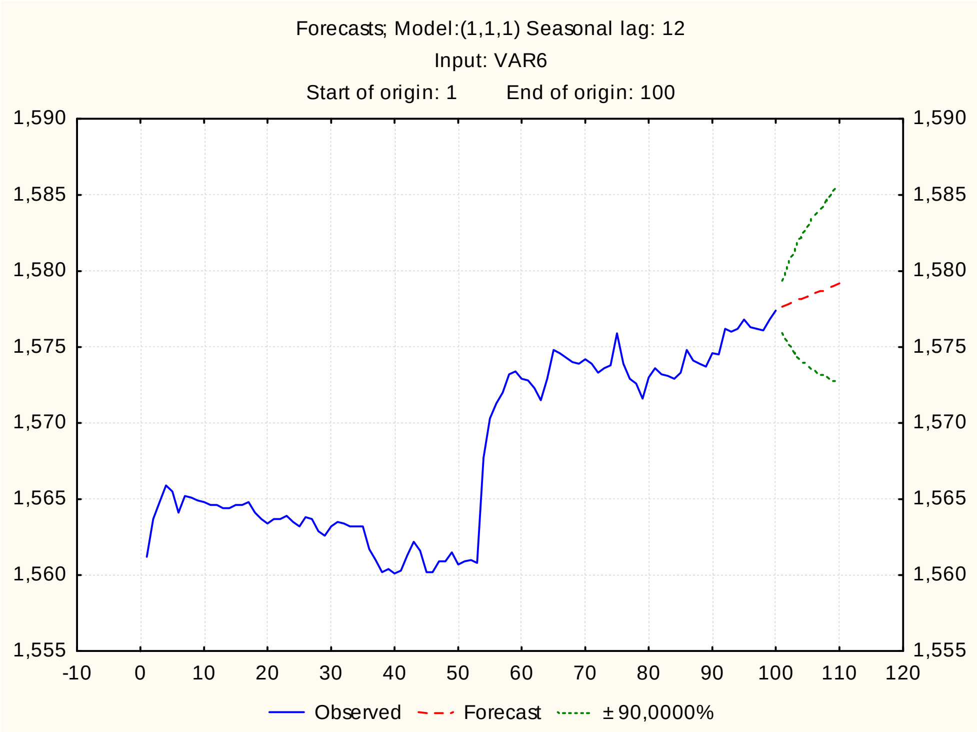


Fig. 27. ARIMA model prediction chart with bounds

CaseNo.	Forecasts; Model:(1,1,1) Seasonal lag: 12 (Input: VAR6 Start of origin: 1 End of origin: 100 Forecast	Lower 90,0000%	Upper 90,0000%	Std.Err.
101	1,577642	1,575922	1,579362	0,001036
102	1,577815	1,575107	1,580524	0,001631
103	1,577986	1,574555	1,581418	0,002066
104	1,578157	1,574130	1,582184	0,002425
105	1,578328	1,573783	1,582873	0,002737
106	1,578498	1,573488	1,583508	0,003016
107	1,578669	1,573234	1,584104	0,003273
108	1,578840	1,573010	1,584670	0,003510
109	1,579011	1,572812	1,585210	0,003732
110	1,579181	1,572634	1,585729	0,003942

Fig. 28. ARIMA – forecast in the first column

There are many advantages of using this financial model. At first, results are in graphic and numeric format. The second advantage is that not only the predicted value is available, but also it's lower and upper 90% bounds and standard error. But the most significant characteristic is that we can predict more than one period ahead. In this case, the first predicted value of MAX was 1,5776, the right historical value is 1,5778. Of course, this model was developed randomly without any close searching and I hope that there exist more successful ARIMA (p,d,q) models suitable for exchange rates.

5.6 GARCH Matlab Toolbox

The MathWorks Matlab R2008a is the contemporary version of this worldwide famous technical and engineering developing environment called simply Matlab (matrix laboratory.). It was released on 1st March 2008. The environment includes a lot of toolboxes which are useful for areas from Aerospace to Virtual Reality. In this part I will try to develop a GARCH model by using commands from GARCH Toolbox 2 and help from its User's Guide. [36]

The first step is import of data from a text file containing 1 934 MAX EUR/USD historical 10 minutes data in one column. Then I plotted data in figure to see the course of observations.

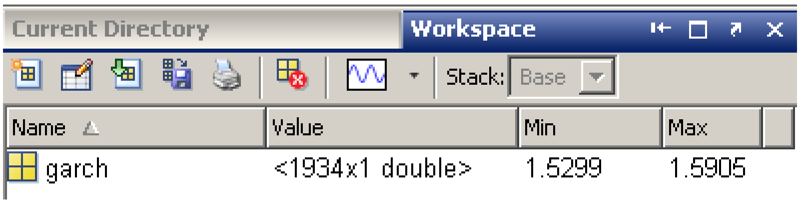


Fig. 29. Imported values in MATLAB Workspace

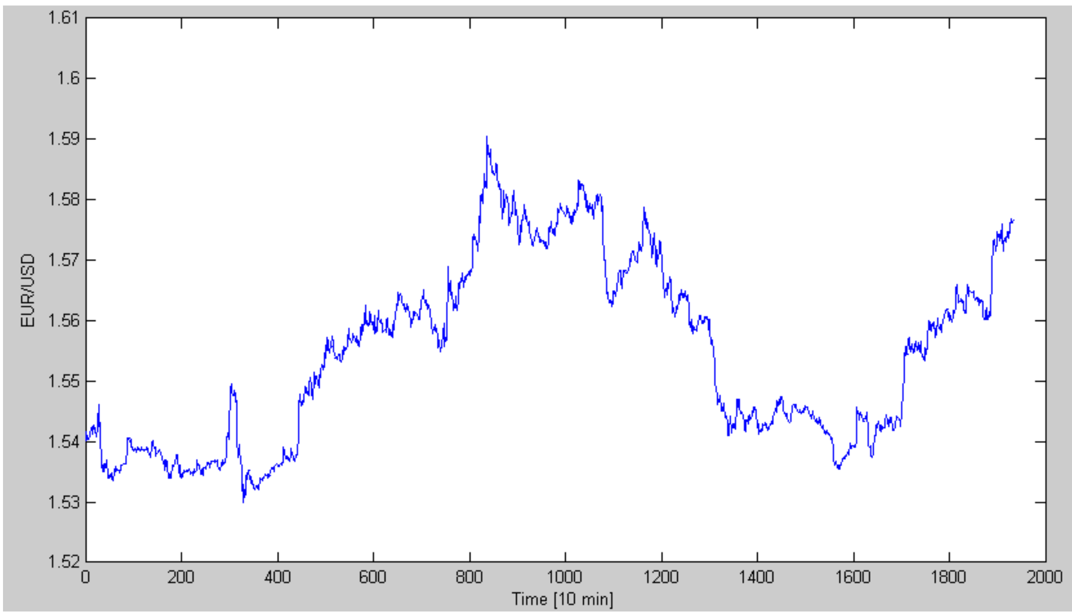


Fig. 30. MATLAB plot of EUR/USD observations

Because GARCH modelling assumes a return series, I need to convert the prices to returns. It is performed by command:

```
eurusd = price2ret(garch);        % Logarithmic returns
```

Now, I used the plot function to see the return series in Figure 31:

```
2       plot(eurusd)
```

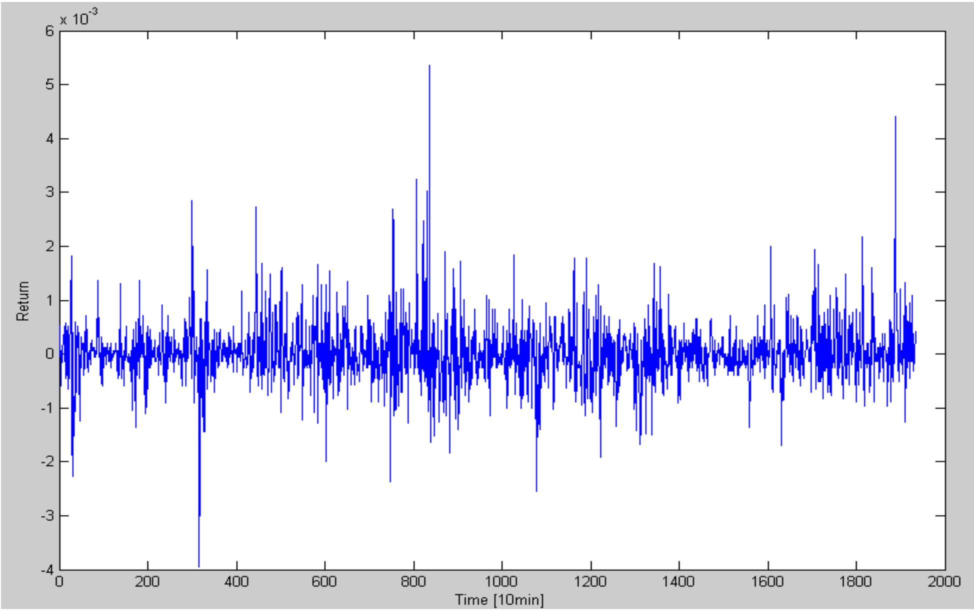


Fig. 31. The raw return series with volatility clustering

Assuming that all autocorrelations are zero beyond lag zero, I used the autocorr function to compute and display the sample ACF of the returns and the upper and lower standard deviation confidence bounds:

```
3       autocorr(eurusd)
```

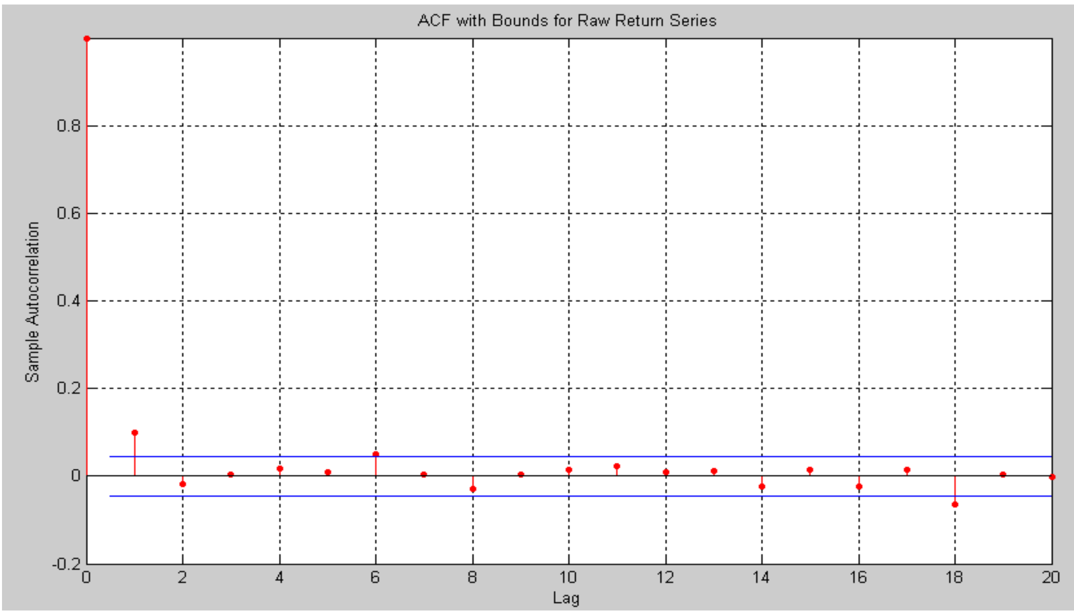


Fig. 32. Autocorrelation function with standard deviation confidence bounds

Then I used the parcorr function to display the sample PACF with upper and lower confidence bounds:

4 `parcorr(eurusd)`

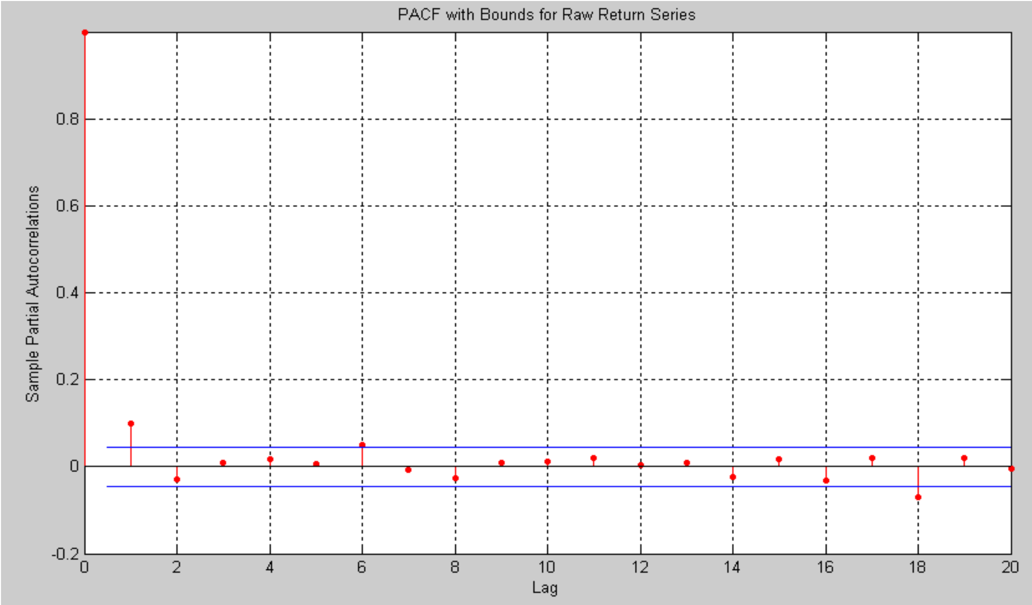


Fig. 33. Partial-autocorrelation function with confidence bounds

Although the ACF of the observed returns exhibits little correlation, the ACF of the squared returns may still indicate significant correlation and persistence in the second-order moments. We can check this by plotting the ACF of the squared returns:

5 `autocorr(eurusd.^2)`

Fig. 34. ACF of the squared returns

The following commands are performed in order to help to estimation function *garchfit* to estimate the model parameters:

```
[coeff,errors,LLF,innovations,sigmas,summary] = ...
garchfit(eurusd);
```

The last command is *garchdisp* function, which displays the parameter estimates and their standard errors. They are listed in the following figure:

```
>> garchdisp(coeff,errors)

 Mean: ARMAX(0,0,0); Variance: GARCH(1,1)

 Conditional Probability Distribution: Gaussian
 Number of Model Parameters Estimated: 4

                                   Standard          T
 Parameter         Value             Error        Statistic
-----------     -----------    -------------    -----------
          C     1.6994e-005      1.2987e-005        1.3085
          K     3.2517e-008      2.4341e-009       13.3586
   GARCH(1)     0.77718          0.012835          60.5507
    ARCH(1)     0.13793          0.012386          11.1362
```

Fig. 35. GARCH(1,1) parameter estimates and their standard errors

From parameters obtained by Matlab the equation of GARCH(1,1) is:

$$
\begin{aligned}
y_t &= 1,6994e^{-005} + \varepsilon_t \\
\sigma^2{}_t &= 3,2517e^{-008} + 0,77718\sigma^2{}_{t-1} + 0,13793\varepsilon^2{}_{t-1}
\end{aligned}
\qquad (17)
$$

There is the possibility to use the *garchplot* function to inspect the relationship between the innovations (residuals) derived from the fitted model, the corresponding conditional standard deviations (sigmas), and the observed returns:

```
garchplot(innovations,sigmas,eurusd)
```

The innovations (shown in the next plot) and the returns (shown in the bottom part of the plot) exhibit volatility clustering.

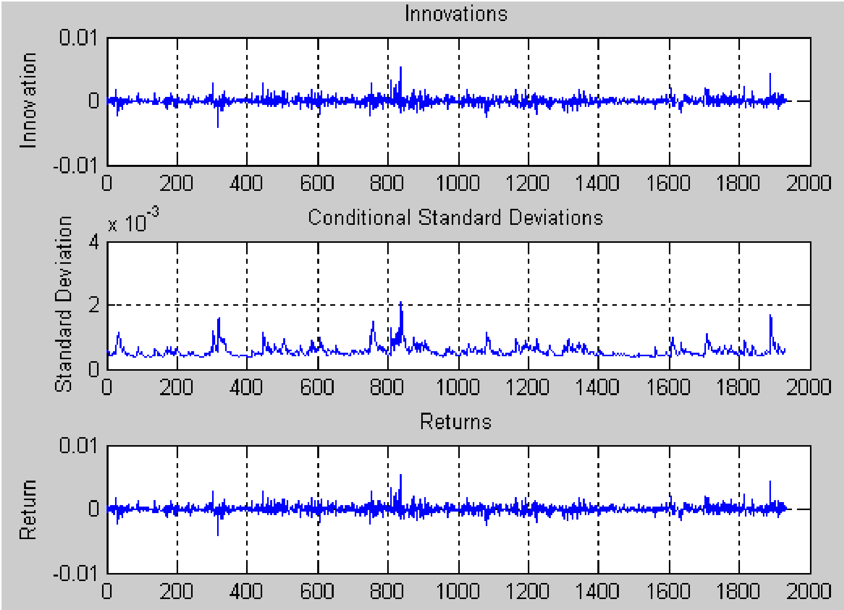


Fig. 36. Comparing of innovations, deviations and returns

The following command is used to forecast the conditional mean and standard deviation in each period of a 10-period forecast horizon:

```
>> [sigmaForecast,meanForecast] = garchpred(coeff,eurusd,10);
[sigmaForecast,meanForecast]

ans =

  4.7793e-004   1.6994e-005
  4.9147e-004   1.6994e-005
  5.0354e-004   1.6994e-005
  5.1434e-004   1.6994e-005
  5.2403e-004   1.6994e-005
  5.3274e-004   1.6994e-005
  5.4058e-004   1.6994e-005
  5.4767e-004   1.6994e-005
  5.5407e-004   1.6994e-005
  5.5986e-004   1.6994e-005
```

Fig. 37. GARCH(1,1) sigma and mean forecast

The result consists of the MMSE (minimum mean-square error) forecasts of the conditional standard deviations and the conditional mean of the return series eurusd for a 10-period default horizon. They show that the default model forecast of the conditional mean is always $C=1.6994.10^{-5}$.

5.7 ANN in Matlab Neural Network Toolbox

Neural Network Toolbox is currently a very sophisticated and practical set of programs for neural networks creation. Two of them will be used for exchange rate prediction – Neural Fitting Tool (nftool) for model training and evaluation, and then Neural Network Tool (nntool) for prediction.

5.7.1 Multiply prediction

Firstly I imported appropriate data. It was from Excel prepared set of 3 173 data inputs in four columns and 1 column for outputs. The columns were last week price, last day, last hour, last ten minutes. The predicted value will be the actual 10 minutes price maximum of EUR/USD. This is the case of mentioned multiply prediction. After the import the data are divided for training, validation and testing and training is performed. For this model I used 20 neurons in hidden layer. The network can be several times retrained if we are not satisfied with results. There is a button Retrain with this function. After this proceeding, data are again randomly divided among training, validation and testing sets. The fitness of network is judged by two indicators – MSE and R.

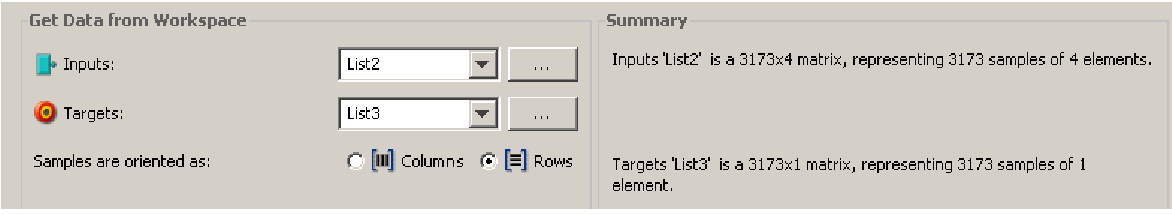


Fig. 38. Import of 3173x4 matrix of inputs and 3173x1 matrix of output data

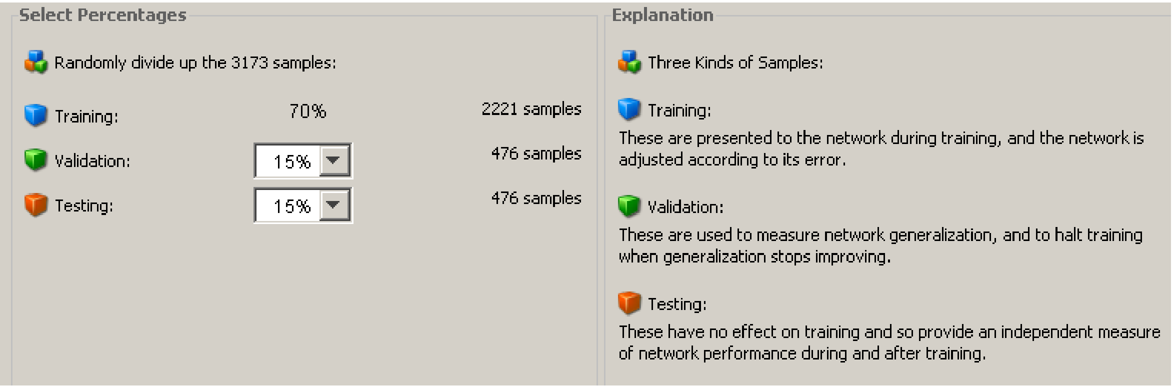


Fig. 39. Dividing data for training, validation and testing

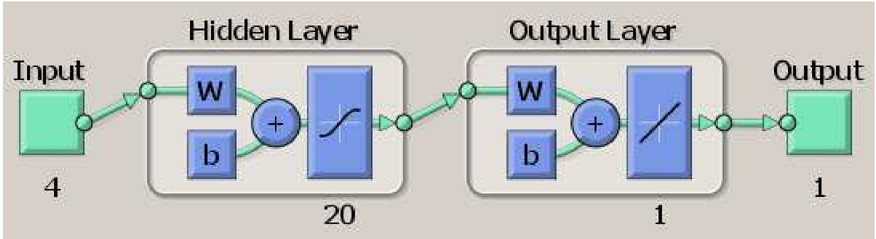


Fig. 40. Scheme of applied network with 20 neurons in hidden layer

Mean squared error quantifies the amount by which the model differs from data, or better said, statistically significant error between model and reality. The lower value is better. Ideal model would have zero MSE value. We can see in the Figure 41 that the error of the multiply model is quite small. However, the network was trained by data only once. The highest order position of the first digit in MSE is for all three operations the 7th after decimal comma. The R stands for correlation between target data (desired output) and the actual output from the network. Ideal value is 1, which means perfect correlation.

Results

	Samples	MSE	R
Training:	2221	5.02545e-7	9.99749e-1
Validation:	476	4.00351e-7	9.99783e-1
Testing:	476	7.40315e-7	9.99624e-1

Fig. 41. Results of training, validation and testing

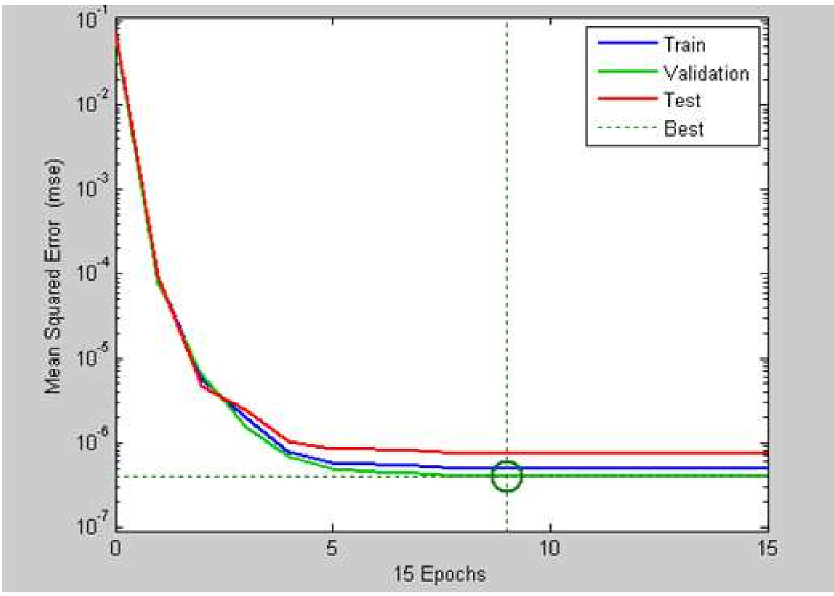


Fig. 42. Mean squared error (MSE) of train, validation and test

Network is trained in epochs and the validation data set in Figure 42 displays that after 9th epoch the network could not been improved by more training. So the training ends and network is tested by putting testing data set on the inputs.

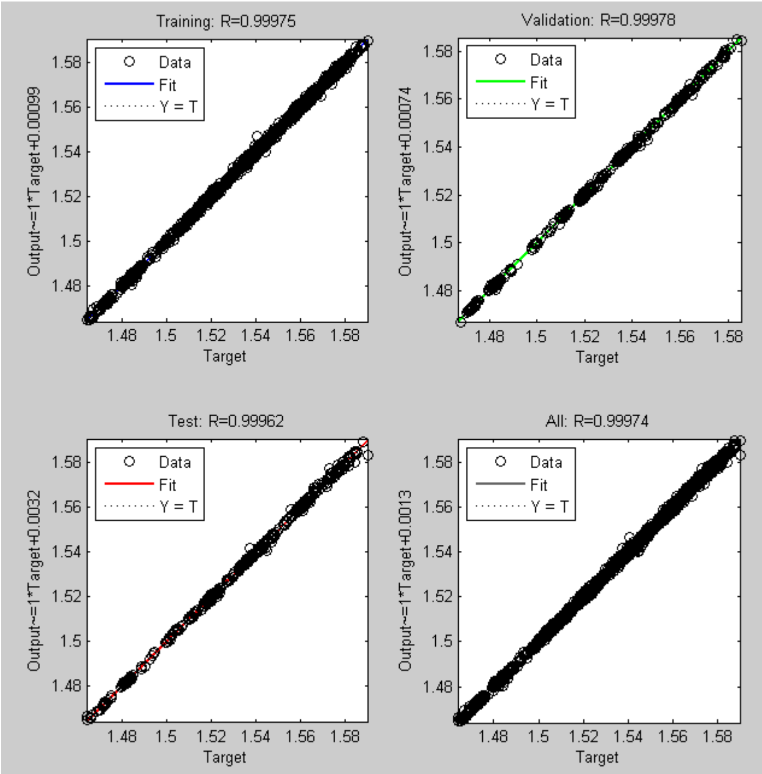


Fig. 43 Regression of training, validation and testing

The Figure 43 represents graphically the binding between target data and output provided by network. The perfect correlation would by a straight line without data variations above and under the line.

The model development is finished and prediction can be performed. If we save at least the network before ending the work with Neural Fitting Tool (nftool), the workspace of Matlab will contain this network and it can be taken over into Neural Network Tool (nntool). We select the option import from workspace.

NNtool is suitable for network model development, too. It offers twenty network types, fourteen training functions, three transfer functions and three performance functions. It is possible to determine the number of layers and number of neurons for the model. When we have the desired network, the prediction is possible. The input data should be imported or put manually in the form of vector, e.g. in my case [1.5905; 1.5833; 1.5794; 1.5773]

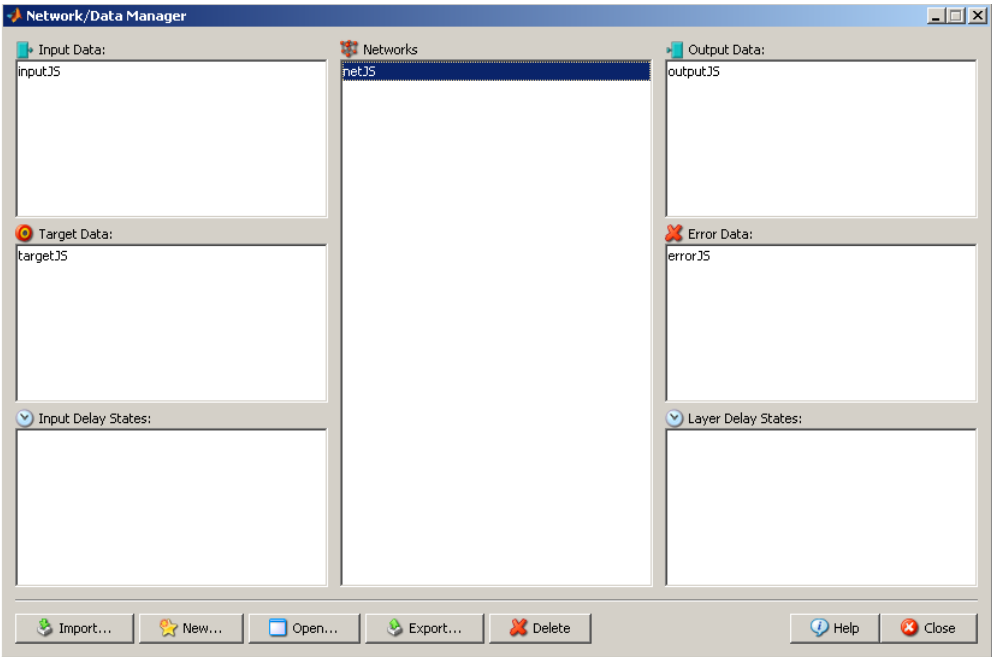


Fig. 44. Neural Network Tool – nntool

The next figure is the result of one period prediction using multiple prediction method. Fifty samples were predicted and compared with historical data. Again the MAX of EUR/USD ten minutes' data was the aim. The model adapted very well and the differences are small and acceptable. The numeric results are included in Table 4.

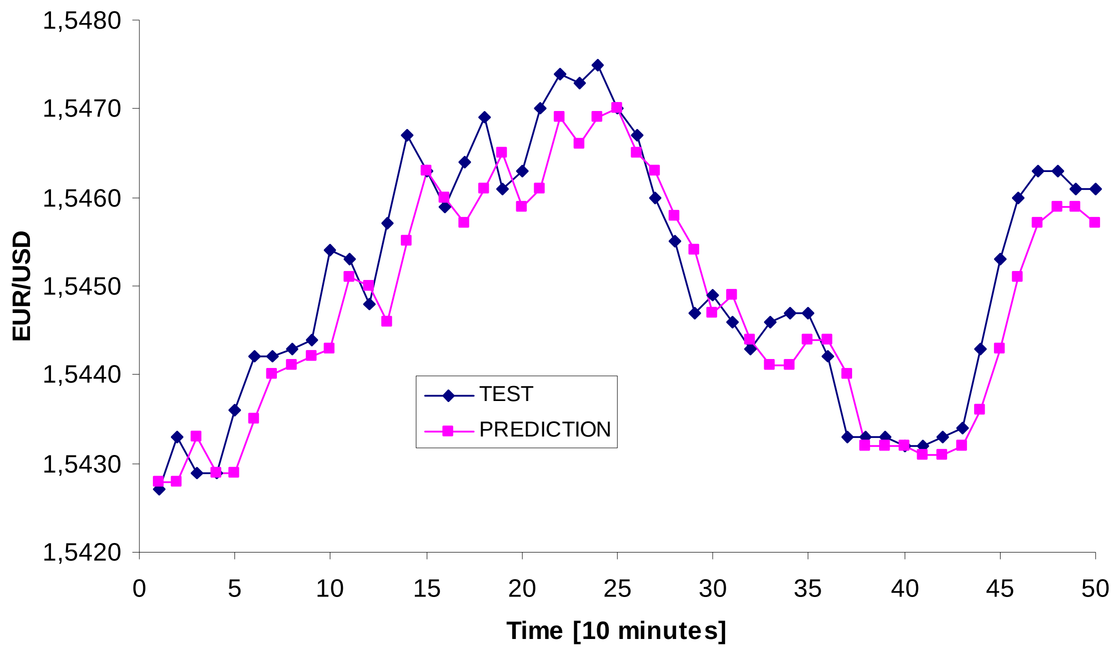


Fig. 45. The comparison of multiple prediction and real historical data

Tab. 4. Ten minutes multiple prediction results

Last week	Last day	Last hour	Last 10 minutes	Actual 10 minutes	Matlab
1.5905	1.5475	1.5429	1.5429	**1,5427**	**1,5428**
1.5905	1.5475	1.5442	1.5427	**1,5433**	**1,5428**
1.5905	1.5475	1.5442	1.5433	**1,5429**	**1,5433**
1.5905	1.5475	1.5442	1.5429	**1,5429**	**1,5429**
1.5905	1.5475	1.5442	1.5429	**1,5436**	**1,5429**
1.5905	1.5475	1.5442	1.5436	**1,5442**	**1,5435**
1.5905	1.5475	1.5442	1.5442	**1,5442**	**1,5440**
1.5905	1.5475	1.5454	1.5442	**1,5443**	**1,5441**
1.5905	1.5475	1.5454	1.5443	**1,5444**	**1,5442**
1.5905	1.5475	1.5454	1.5444	**1,5454**	**1,5443**
1.5905	1.5475	1.5454	1.5454	**1,5453**	**1,5451**
1.5905	1.5475	1.5454	1.5453	**1,5448**	**1,5450**
1.5905	1.5475	1.5454	1.5448	**1,5457**	**1,5446**
1.5905	1.5475	1.5469	1.5457	**1,5467**	**1,5455**
1.5905	1.5475	1.5469	1.5467	**1,5463**	**1,5463**
1.5905	1.5475	1.5469	1.5463	**1,5459**	**1,5460**
1.5905	1.5475	1.5469	1.5459	**1,5464**	**1,5457**
1.5905	1.5475	1.5469	1.5464	**1,5469**	**1,5461**
1.5905	1.5475	1.5469	1.5469	**1,5461**	**1,5465**

5.7.2 Auto-prediction in MATLAB

According to the theory, auto-prediction should give worse results than multiple predictions with one step. However, the great advantage of this technique is that we can forecast more than one period ahead and thus better see what will happen on the market few steps in the future. In order to keep the same conditions, I will use the same data set of MAX, shifted for one step between input data and target data. Then the first predicted output from the finished network will be used as a new input and so on. Again nftool and nntool are utilized. The input matrix will contain 2 columns of 3173 data and target the MAX shifted by one period ahead. The second column in input will be order number of MAX instead of time (that means nonnegative integer numbers from 1 to 3173).

The second auto-prediction test will use 2 inputs to help improve the results. The MAX and the time in number format, because the time is changing constantly and it does not need to be predicted. The problem is that time in number format with 10 minutes period has only 24*6=144 values in a single day. Then Excel starts new data round from 0 (00:00:01) to 1 (both rounded). So as input I will use time from 00:00:01 till 19:00:01 and then we can predict 30 values till midnight of the trading day.

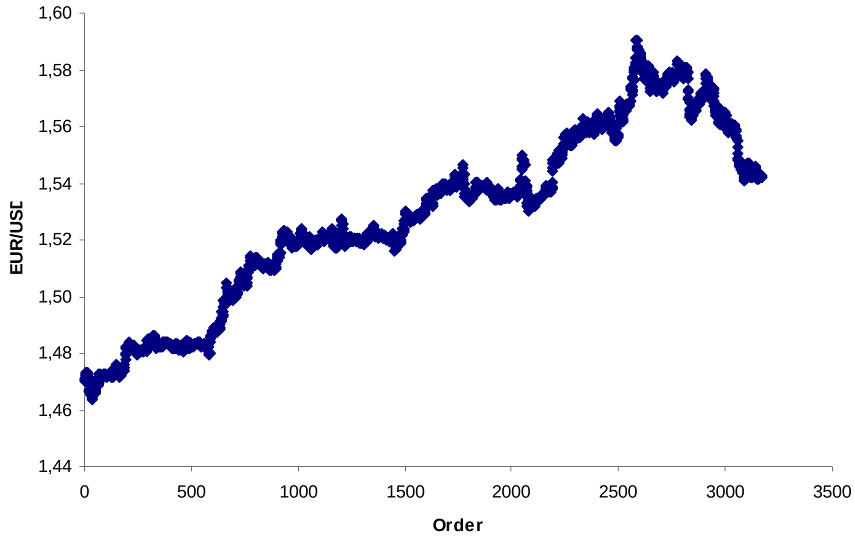
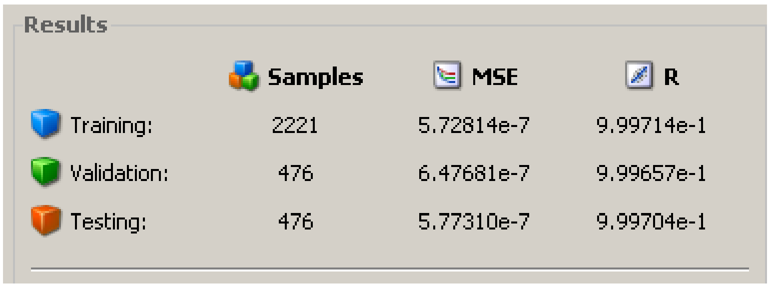


Fig. 46. Input data set for the 1st auto-prediction test



Results

	Samples	MSE	R
Training:	2221	5.72814e-7	9.99714e-1
Validation:	476	6.47681e-7	9.99657e-1
Testing:	476	5.77310e-7	9.99704e-1

Fig. 47. Results of network estimation – 1st auto-prediction

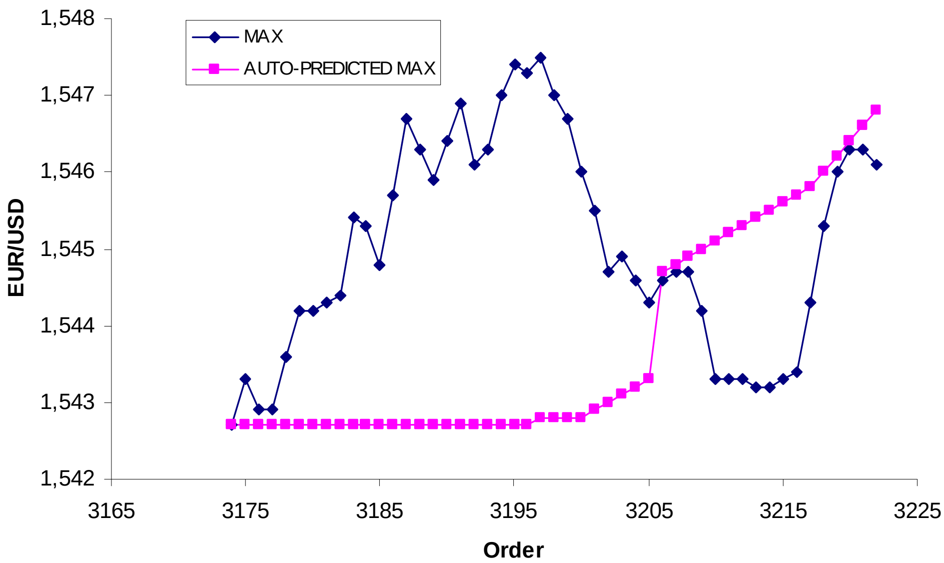


Fig. 48. Auto-prediction in chart

The Figure 48 proves that that the network performed not very well. Maybe it was over fitted, which means that too long time series were used for modelling. Let’s try auto-predictive model with shorter training and validation set (115 values). The results are surprisingly not good, although correlations R are high and MSE is low. Auto-prediction is surely not acceptable method.

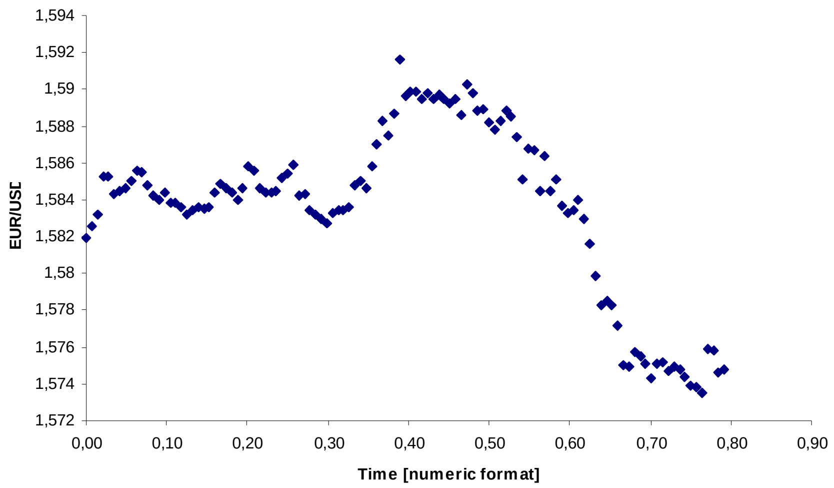


Fig. 49. Input data set for the 2nd auto-prediction test

Results

	Samples	MSE	R
Training:	81	3.91935e-7	9.91826e-1
Validation:	17	3.54247e-7	9.89220e-1
Testing:	17	4.34216e-7	9.92568e-1

Fig. 50. Results of network estimation – 2nd auto-prediction

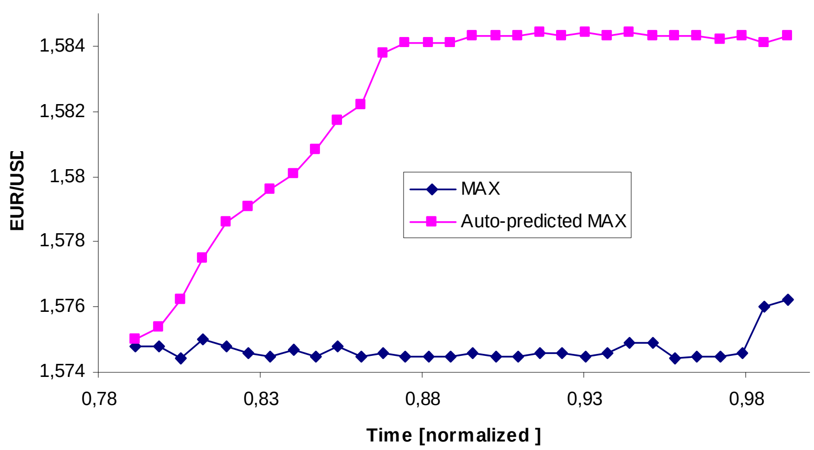


Fig. 51. Auto-prediction in chart – second sample

5.8 ANN in Mathematica 5.2

Founded by Stephen Wolfram in 1987, Wolfram Research is one of the world's most respected software companies. Their product Mathematica is the powerful global computation system. Neural Networks is a Mathematica package designed to train, visualize, and validate neural network models. [41]

5.8.1 Linear ANN – 10 minutes prediction

The original example of linear neural network prediction comes from [41]. I used my own data and increased the number of time base periods. Linear ANN means that NN does not have hidden layer, it includes only 4 input neurons and 1 output neuron. In the first example I mention also source code of the NN creation used in command line of the program.

Data for 10 minutes prediction were imported to Excel and with its function CONCATENATE the set of 7257 vectors in one column was put together. The one vector contains five values and the numbers are volume, open, close, min and predicted MAX.

$$\{75,1.5779,1.579,1.5778,1.579\} \tag{18}$$

The big vector was copied to common text file. After opening a new notebook in Mathematica we will use the following commands:

8
```
In[1]:= << NeuralNetworks`
```
9
```
In[2]:= << LinearAlgebra`MatrixManipulation`
```
10
```
In[3]:= << math10min.txt;
```

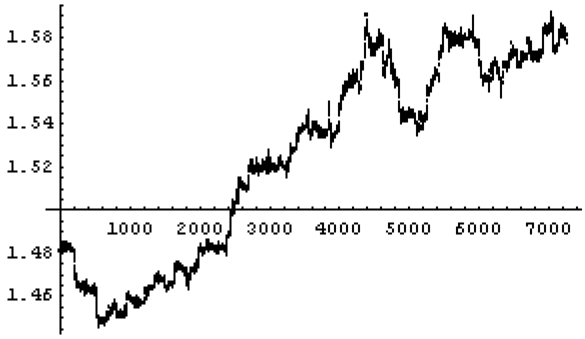
At first the packages NeuralNetworks and Linear Algebra are started and the file with vector is imported to the programs memory.

11
```
In[4]:= Dimensions[yeurusd]

Out[4]= {7257, 5}
```

The command Dimensions has the size of the vector as its output. It is 7257 rows and 5 columns.

12
```
In[5]:= ListPlot[Flatten[TakeColumns[yeurusd, {5}]]]
```




```
Out[5]= - Graphics -
```

ListPlot plots the imported data; in this case it is the fifth column – MAX. The “x” axis is the day number.

13
```
In[6]:= u = TakeColumns[yeurusd, {1, 4}];

In[7]:= y = TakeColumns[yeurusd, {5}];
```

The above commands divide the columns into input and output.

14
```
In[8]:= ue = u[[Range[5442]]];

In[9]:= ye = y[[Range[5442]]];

In[10]:= uv = u[[Range[5443, 7257]]];

In[11]:= yv = y[[Range[5443, 7257]]];
```

The commands In[8] to In[11] divide the data into training and validation sets.

15
```
In[12]:= {model1, fitrecord} = NeuralARXFit[ue, ye, {{1}, {1, 1, 1, 1}, {1, 1, 1, 1}},
    FeedForwardNet, {}, CriterionPlot → False];

NeuralFit::LS :
 The model is linear in the parameters. Only one training iteration is necessary
  to reach the minimum. If no training iteration was performed, it is
  because the fit was completed during the initialisation of the network.
```

A linear model for the currency prediction is estimated. The type of the network is feed forward. The four parameters are estimated for input variables.

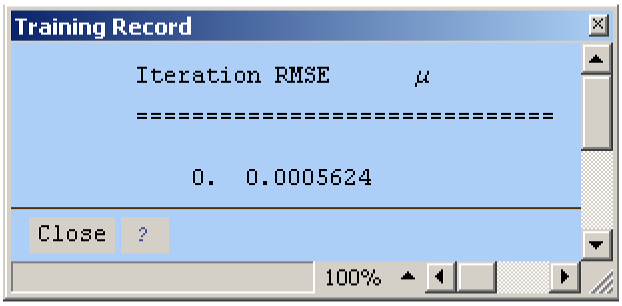


Fig. 52. Root mean square error

After estimation the dialog with RMSE information appears. The first digit is on the fourth place after comma. The RMSE characterizes the error rat of the model. The next code finally displays the linear parameters estimation of the model.

16
```
In[14]:= model1[[1]][{yy[t - 1], u1[t - 1], u2[t - 1], u3[t - 1], u4[t - 1]}]

Out[14]= {-0.0012495 + 1.82846 × 10^-7 u1[-1 + t] - 0.0434768 u2[-1 + t] +
    0.90015 u3[-1 + t] - 0.0434093 u4[-1 + t] + 0.1878 yy[-1 + t]}
```

If we need more accurate numbers, pressing the Enter button displays the extended equation:

17
```
{-0.0012495007487762622` + 1.8284615123111118`*^-7 u1[-1 + t] -
  0.0434768425916287` u2[-1 + t] + 0.9001500733753477` u3[-1 + t] -
  0.04340931767986453 6` u4[-1 + t] + 0.18779952761389565` yy[-1 + t]}
```

The symbols u1 to u4 stand for our inputs volume, open, close and min. The term in brackets stands for time, that is, one period back, so we fill actual inputs and then get one step prediction as output. The symbol yy stands for previous output or real observation of MAX. Of course, it is better to substitute it for real observations; otherwise it would be partial auto-prediction. The next two functions write out information about network.

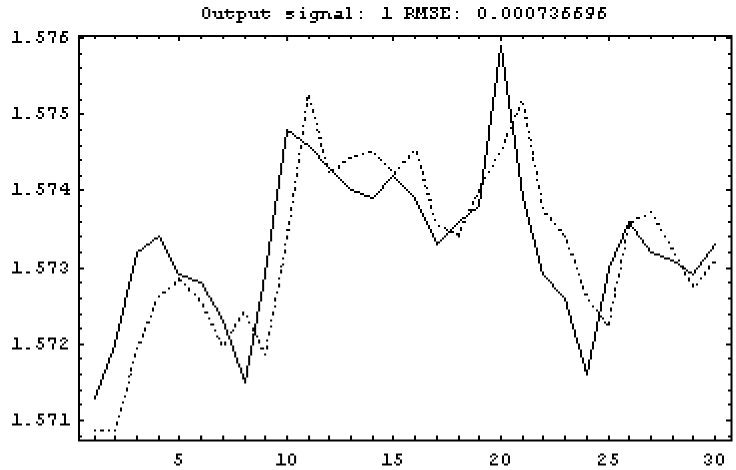
18
```
In[16]:= NetInformation[model1]

Out[16]= NeuralARX model with 4 input signals and 1 output signal.
    The regressor is defined by: na = {1}, nb = {1, 1, 1, 1},
    nk = {1, 1, 1, 1}. The mapping from regressor to output is
    defined by a FeedForward network created 2008-4-29 at 8:03.
    The network has 5 inputs and 1 output. It has no hidden layer.
```

19
```
In[17]:= NNModelInfo[model1]

Out[17]= NNModelInfo[NeuralARX[FeedForwardNet[{{w1}}, {AccumulatedIterations → 0,
     CreationDate → {2008, 4, 29, 8, 3, 52.0156250},
     Neuron → Sigmoid, FixedParameters → None,
     OutputNonlinearity → None, NumberOfInputs → 5}],
   Regressor → {{1}, {1, 1, 1, 1}, {1, 1, 1, 1}}]]
```

20 In[15]:= NetComparePlot[uv, yv, model1, PredictHorizon → 1, ShowRange → {1, 30}]



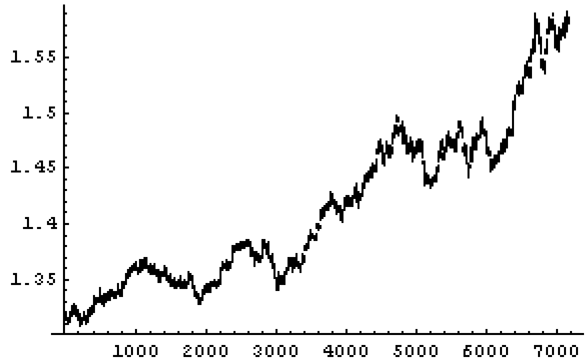
Out[15]= - Graphics -

The function above evaluates the one-step prediction on validation data. The plot shows the predicted rate (dotted line) together with the true rate. The RMSE of the prediction is also given, and we can also use it as a measure of the quality of the predictor.

5.8.2 Linear ANN – 1 hour prediction

The second prediction with Mathematica Neural Networks is for one hour prediction step. Training data are again shown by function Listplot.

21 In[21]:= ListPlot[Flatten[TakeColumns[yeurusd, {5}]]]



Out[21]= - Graphics -

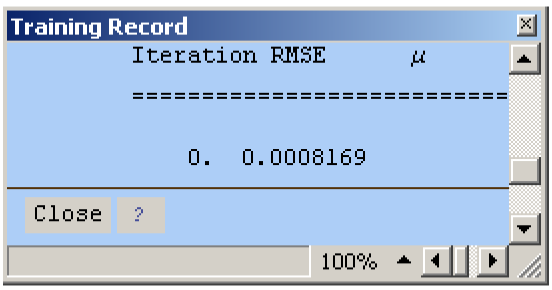


Fig. 53. RMSE – hour data training

22

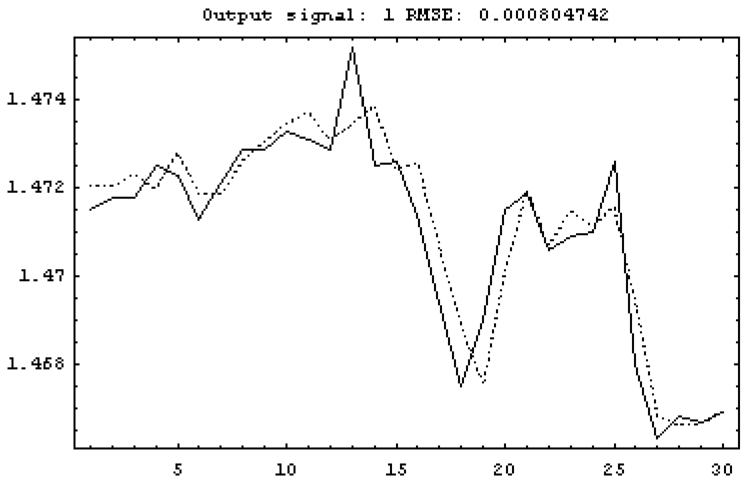
```
In[29]:= model2[[1]][{yy[t - 1], u1[t - 1], u2[t - 1], u3[t - 1], u4[t - 1]}]

Out[29]= {-0.00118609 + 8.4222 × 10^-8 u1[-1 + t] - 0.0410585 u2[-1 + t] +
    0.923876 u3[-1 + t] - 0.0218708 u4[-1 + t] + 0.140291 yy[-1 + t]}
```

The meanings of symbols in the above equation are the same as in equation for model 1, only parameters are different. When we compare first (model 1) and second (model 2) equations, we can specify what inputs have the largest effect on output. Surely, the greater the parameter is, the bigger the effect on output. It is the input u3 with approximately 0,90 and more effect on the output. U3 stand here for close price of EUR/USD. The smallest effect is from the volume u1, it is almost zero. NetComparePlot function compares 30 predicted values with real values from validation set. Predicted is dotted line.

23

```
In[30]:= NetComparePlot[uv, yv, model2, PredictHorizon → 1,
    ShowRange → {1, 30}]
```




```
Out[30]= - Graphics -
```

5.8.3 Linear ANN – 1 day prediction

Everything what was mention about model 1 and model 2 is applied also for daily data prediction in model 3. A new piece of finding is that RMSE increases with longer period.

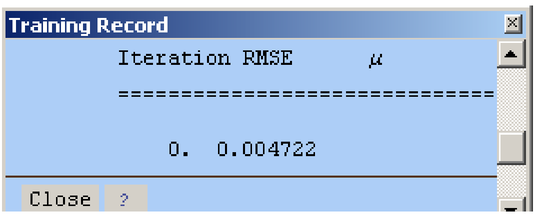
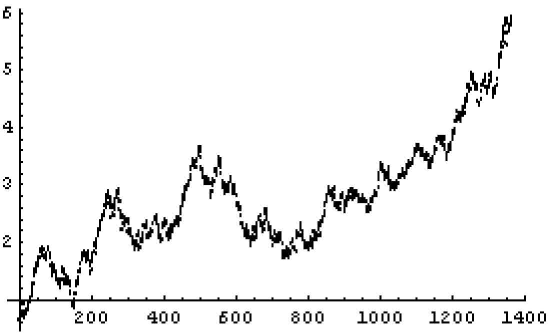


Fig. 54. RMSE – daily data training

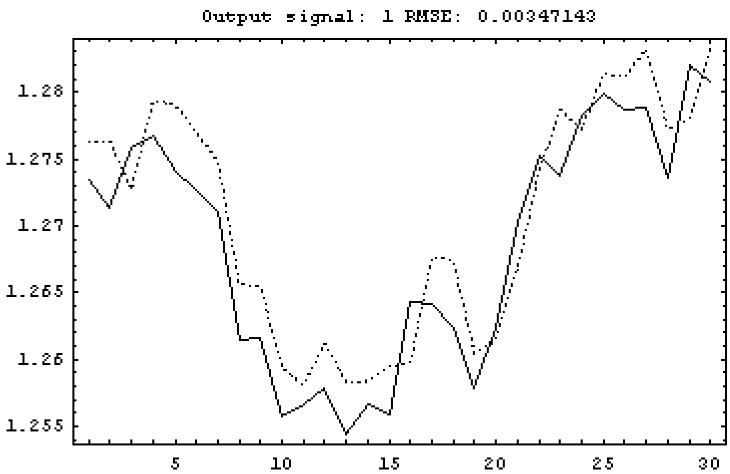
24 In[36]:= **ListPlot[Flatten[TakeColumns[yeurusd, {5}]]]**



25 In[44]:= **model3[[1]][{yy[t - 1], u1[t - 1], u2[t - 1], u3[t - 1], u4[t - 1]}]**

Out[44]= $\{0.0111871 - 7.35079 \times 10^{-9}\, u1[-1+t] - 0.0226932\, u2[-1+t] + 0.864874\, u3[-1+t] + 0.143984\, u4[-1+t] + 0.0103468\, yy[-1+t]\}$

26 In[45]:= **NetComparePlot[uv, yv, model3, PredictHorizon → 1, ShowRange → {1, 30}]**



Out[45]= - Graphics -

The validation of one day data was performed quite well especially in linear parts.

All three models will be evaluated as examples in the project part of the thesis. The linear NN surprised me with simplicity and effectiveness if fitting. No hidden neurons were needed. However, NeuralARXFit function used for fitrecord of model enables to enter the number of neurons in hidden layer, after the sequence FeedForwardNet, in to the empty brackets. I tested several numbers of hidden neurons but the results of fitting and prediction were similar to the network without hidden neuron layer.

5.9 Statistica Neural Networks

Statistica Neural Networks is a tool for solving problems from various areas. I will use it for automatic network creation with Intelligent Problem Solver. The menu for ANN is surely rich in items and it would take maybe one hundred lists of paper to demonstrate what is possible to do with it.

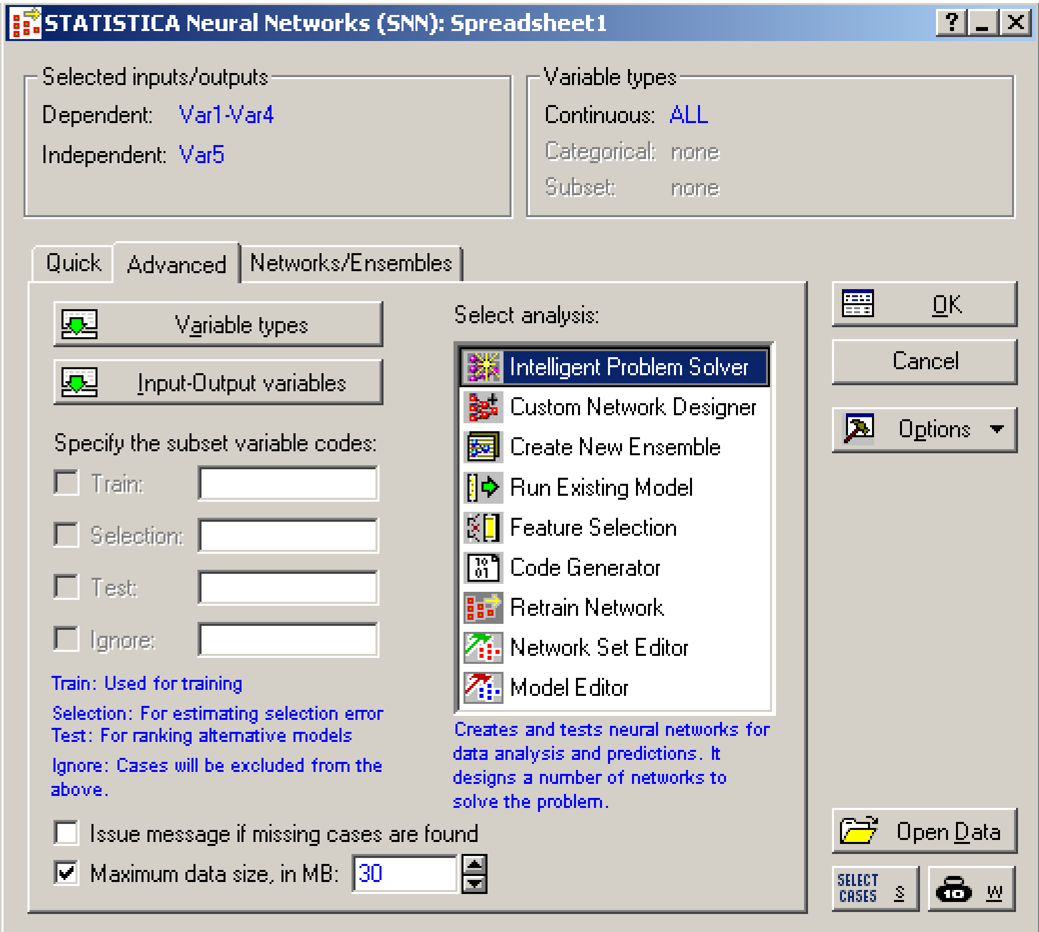


Fig. 55. Start up dialog box of Statistica NN

The set of 3173 data vectors was copied into Statistica spreadsheet. It is easy to process data like in Microsoft Excel. The five columns were volume, open, close, min and MAX. Then Statistics – Neural Networks dialog box is started from the menu (Figure 55). We set the variables types as continuous and Var1 to Var4 as inputs and Var5 as output. After OK click another settings are available. The most important is how Intelligent Problem Solver will search for the best network type according to data provided in Statistica spreadsheet. Automatically many networks are used on data and the five with smallest error are the winners. Optimization of network structure (type of network, number of layers, and number of neurons in layers) can be performed with specifying the time in hours and minutes or by setting the number of networks to be tested on data (Figure 56). For this example I used ten minutes optimization, it is possible to test for several hours. This is a small disadvantage of NN that sometimes they are time consuming.

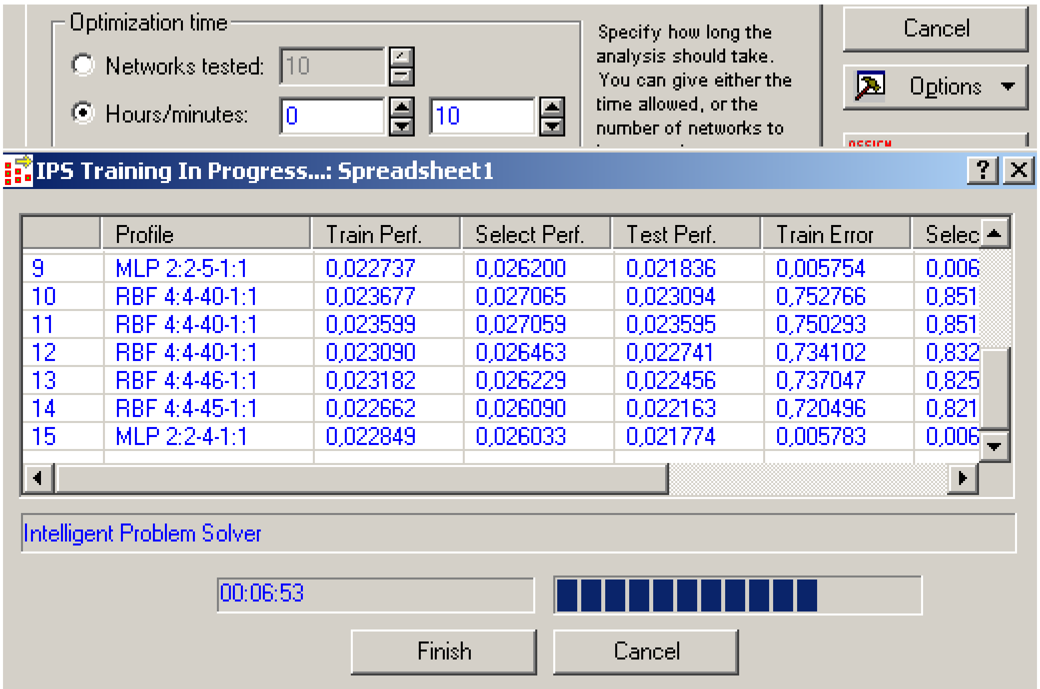


Fig. 56. Intelligent Problem Solver in action

Optimization by setting number of networks to be tested to 10 lasted only several seconds. Here it is important to emphasize that the best computer hardware is favourable.

Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error
1	RBF 4:4-45-1:1	0,022662	0,026090	0,022163	0,720496	0,821341
2	MLP 2:2-3-1:1	0,024226	0,027023	0,022785	0,006131	0,006770
3	MLP 2:2-4-1:1	0,022849	0,026033	0,021774	0,005783	0,006522
4	Linear 2:2-1:1	0,022631	0,025989	0,021704	0,005728	0,006511
5	Linear 3:3-1:1	0,022619	0,025970	0,021675	0,005725	0,006506

Fig. 57. Five best network types in Statistica NN

The five best network types according to Intelligent Problem Solver are suitable for further examination. We can visualize correlations, observed and predicted data, retrain networks and many more. The descriptive statistics, sensitivity analysis, residuals and various plots are available. User defined case is very important for prediction. Here the user will put his observed 4 input variables and then Prediction button will show prediction by five best networks (Figure 59). Thus the prediction is not performed only by one network. It is ideal if we do not trust one neural network very well and we can consider neural networks as real experts in data prediction by using Delphi method. According to this method, the best prediction would be democratically the majority opinion of five networks. This is the connection with thinking about NN as artificial intelligence elements.

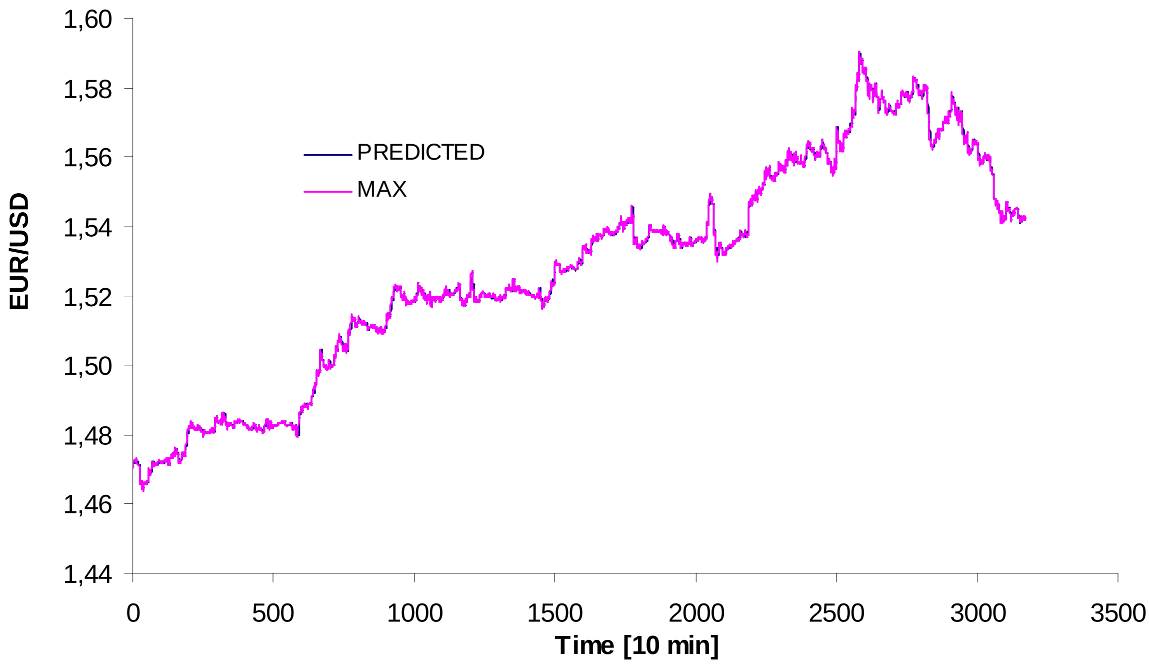


Fig. 58. Training data fitting of one multilayer network

The above figure shows the training results of one multilayer network on the data. Practically the two lines seem to be identical, but they are not. Only the difference or error is so small. For example, the value of the 1000th data is 1,5185 for real MAX historical observations and 1,5181 for predictor after training.

	User Defined Case Prediction, (1-5) (Spreadsheet1.s				
	Var5.1	Var5.2	Var5.3	Var5.4	Var5.5
1	1,470882	1,476087	1,471432	1,471000	1,470987
2	1,470882	1,476087	1,471432	1,471000	1,470987
3	1,470882	1,476087	1,471432	1,471000	1,470987

Fig. 59. Prediction by five best networks

Intelligent Problem Solver also shows that NN learn from data. The predefined types of networks and their structure can save our time for testing and searching for the best types. The cue is that we can not use one type of NN universally for all currency exchange pairs. Also the time sampling of data and the period generally need to be considered. The type which works today does not have to function tomorrow. The models must be estimated regularly and properly, according to what data are available.

5.10 NeuroSolutions 5 and TradingSolutions 4

Matlab Neural Network Toolbox, Mathematica Neural Networks and Statistica Neural Networks are packages of their respective software platform. The producers of these platforms do not entirely specialize only in these packages, but also in many various technical, engineering and statistical applications. The advanced software is the one from a producer investing all his financial and human capital in developing specialized software for NN modelling. Such a company is for example NeuroDimension and their product line NeuroSolutions and TradingSolutions, available at <http://www.nd.com/>.

Product line NeuroSolutions 5 is divided into products NeuroSolutions, NeuroSolutions for Excel and NeuroSolutions for MATLAB. The first is the base and the two others are plug-ins. NeuroSolutions offers for example network training with genetic algorithms (Figure 60). Genetic algorithms are the second basic element of artificial intelligence. The results from NeuroSolutions for Excel are similar to the Statistica and Mathematica results.

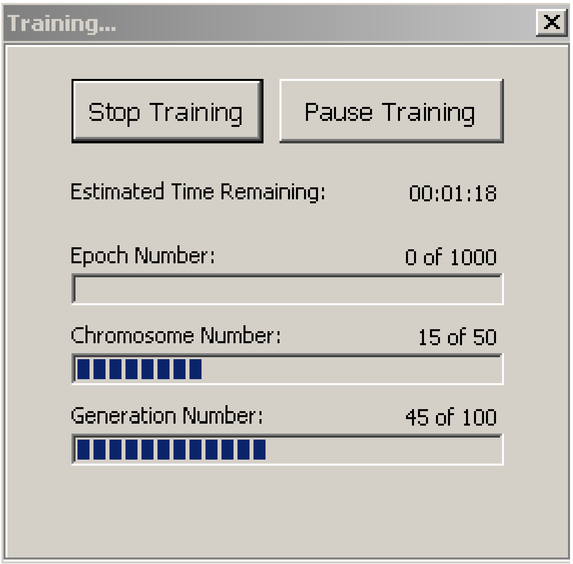


Fig. 60. Training with genetic algorithms

On the other hand, TradingSolutions combines technical analysis with artificial intelligence technologies using neural networks and genetic algorithms to learn patterns from historical data and optimize system parameters. This trading software works with stocks, futures, currencies (FOREX) and many other financial instruments. It can also build systems for U.S. and international markets. I downloaded demo version but I could not evaluate it because it serves as a demonstration copy of its possibilities. The demo claims that there is the possibility to predict patterns known from technical analysis.

6 PROJECT ON IMPLEMENTATION OF PREDICTION METHODS

6.1 Trading Signals

If we decide for any method suitable for trading, the thing that the firm trading on the forex market is interested in are trading signals or trading opportunities. According to developed models I chose three cases made by Mathematica and one made by WinQSB. All of them were computed in Excel from the equations derived with the help of software. Models made with other software would be more time consuming (e.g. Matlab).

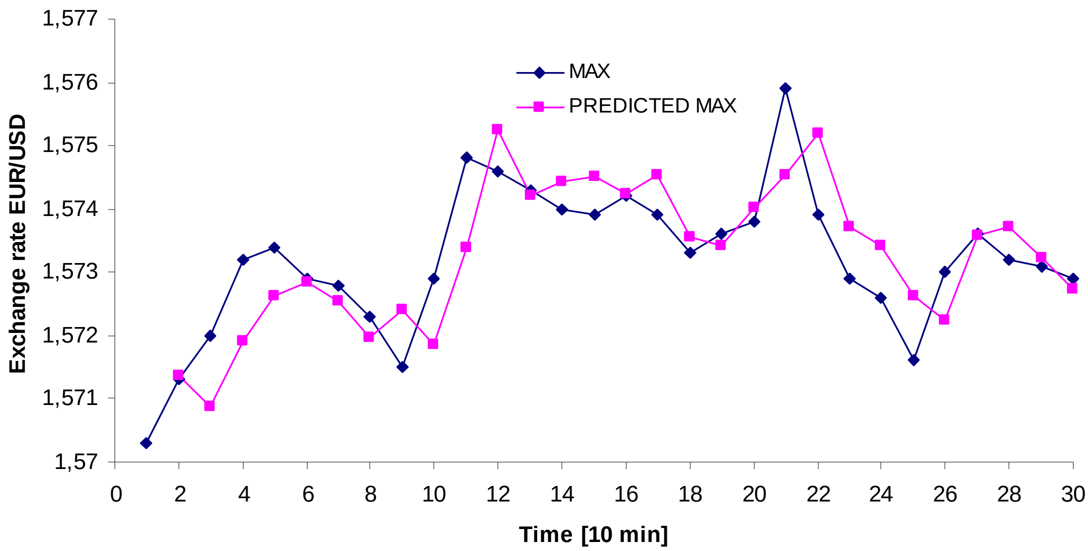


Fig. 61. Mathematica NN - 10 minutes model prediction

Tab. 5. Mathematica - 10 minutes trading signals (green: sell USD, red: buy USD)

Time [10 min]	Volume	Open	Close	Min	Max	Predicted	Difference
1	2806	1,5668	1,5701	1,5663	**1,5703**		
2	3167	1,5698	1,5695	1,5684	**1,5713**	**1,5714**	**-0,0001**
3	3127	1,5692	1,5705	1,5685	**1,572**	**1,5709**	**0,0011**
4	3028	1,5705	1,5712	1,5703	**1,5732**	**1,5719**	**0,0013**
5	2756	1,5713	1,5715	1,5702	**1,5734**	**1,5726**	**0,0008**
6	2428	1,5718	1,5714	1,5709	**1,5729**	**1,5728**	**0,0001**
7	3001	1,5714	1,5706	1,5701	**1,5728**	**1,5726**	**0,0002**
8	2339	1,5706	1,5713	1,5701	**1,5723**	**1,5720**	**0,0003**
9	2190	1,5714	1,5709	1,5697	**1,5715**	**1,5724**	**-0,0009**
10	1736	1,5709	1,5724	1,5704	**1,5729**	**1,5719**	**0,0010**
11	2954	1,5726	1,574	1,572	**1,5748**	**1,5734**	**0,0014**
12	2365	1,574	1,5731	1,5726	**1,5746**	**1,5753**	**-0,0007**
13	2145	1,5729	1,5734	1,5726	**1,5743**	**1,5742**	**0,0001**
14	1992	1,5732	1,5736	1,5726	**1,574**	**1,5744**	**-0,0004**
15	1649	1,5738	1,5734	1,5728	**1,5739**	**1,5745**	**-0,0006**

The invested amount of USD is 100 000. Profit from that operation would be maximally 200 USD. It depends on volatility and only GARCH model can show us how volatile the market will be in next periods.

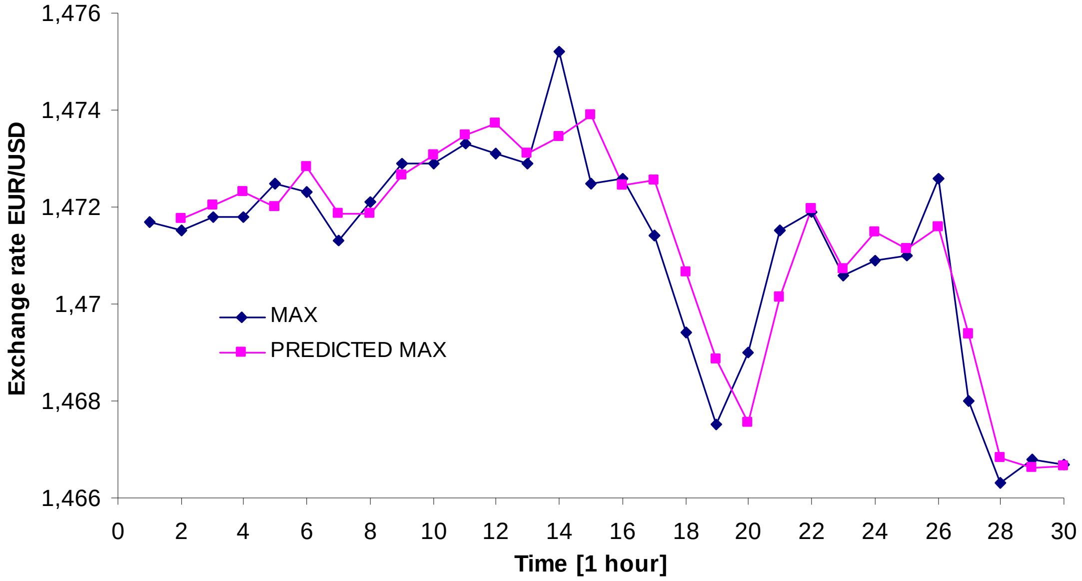


Fig. 62. Mathematica NN – 1 hour model prediction

Tab. 6. Mathematica – 1 hour trading signals (green: sell USD, red: buy USD)

Time [1 hour]	Volume	Open	Close	Min	Max	Predicted	Difference
11	2215	1,4724	1,4728	1,4719	**1,4733**	**1,4735**	**-0,0002**
12	2732	1,4726	1,4721	1,4718	**1,4731**	**1,4737**	**-0,0006**
13	2687	1,472	1,4725	1,4718	**1,4729**	**1,4731**	**-0,0002**
14	9667	1,4726	1,472	1,4714	**1,4752**	**1,4735**	**0,0017**
15	8259	1,4719	1,4709	1,4698	**1,4725**	**1,4739**	**-0,0014**
16	7123	1,4709	1,4711	1,4705	**1,4726**	**1,4724**	**0,0002**
17	8947	1,471	1,469	1,4682	**1,4714**	**1,4726**	**-0,0012**
18	8121	1,4692	1,4673	1,4659	**1,4694**	**1,4707**	**-0,0013**
19	7692	1,4672	1,4661	1,4652	**1,4675**	**1,4689**	**-0,0014**
20	6911	1,4659	1,4687	1,4657	**1,469**	**1,4675**	**0,0015**
21	7618	1,4686	1,4704	1,4679	**1,4715**	**1,4701**	**0,0014**
22	7526	1,4703	1,4691	1,4689	**1,4719**	**1,4720**	**-0,0001**
23	5966	1,469	1,4702	1,4689	**1,4706**	**1,4707**	**-0,0001**
24	5184	1,47	1,4699	1,4686	**1,4709**	**1,4715**	**-0,0006**
25	3813	1,4698	1,4705	1,4694	**1,471**	**1,4711**	**-0,0001**

Profit from the operation based on hour's prediction of MAX would be maximally 300 USD. Of course, it depends on concrete time series. This is only application example.

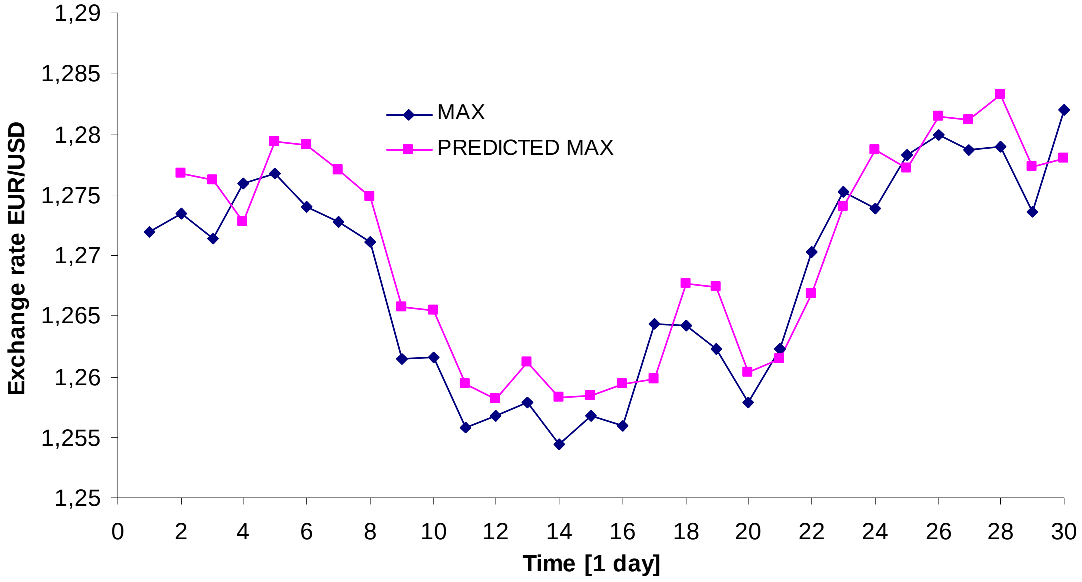


Fig. 63. Mathematica NN – 1 day model prediction

Tab. 7. Mathematica – 1 day trading signals (green: sell USD, red: buy USD)

Time [1 day]	Volume	Open	Close	Min	Max	Predicted	Difference
16	73208	1,2538	1,2541	1,2497	**1,2559**	**1,2594**	**-0,0035**
17	72972	1,2541	1,2626	1,253	**1,2643**	**1,2598**	**0,0045**
18	74228	1,2626	1,2614	1,2595	**1,2642**	**1,2677**	**-0,0035**
19	86611	1,2614	1,2545	1,2531	**1,2623**	**1,2674**	**-0,0051**
20	77620	1,2546	1,2557	1,2521	**1,2578**	**1,2604**	**-0,0026**
21	83885	1,2551	1,2614	1,2551	**1,2623**	**1,2615**	**0,0008**
22	87866	1,2614	1,2689	1,2607	**1,2703**	**1,2668**	**0,0035**
23	88992	1,2688	1,2736	1,2659	**1,2753**	**1,2740**	**0,0013**
24	86191	1,2736	1,2714	1,2695	**1,2738**	**1,2787**	**-0,0049**
25	81180	1,2715	1,2764	1,2677	**1,2783**	**1,2772**	**0,0011**
26	80101	1,2763	1,2752	1,2736	**1,2799**	**1,2814**	**-0,0015**
27	87390	1,2753	1,2777	1,2733	**1,2787**	**1,2811**	**-0,0024**
28	77388	1,2773	1,2717	1,2679	**1,2789**	**1,2832**	**-0,0043**
29	77607	1,2716	1,2723	1,2686	**1,2736**	**1,2773**	**-0,0037**
30	88183	1,2726	1,2778	1,2719	**1,282**	**1,2780**	**0,0040**

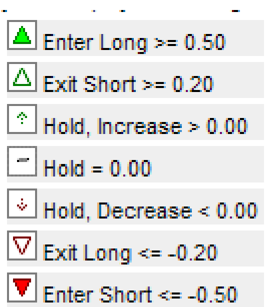


Fig. 64. Trading Solutions signals

Trading signals symbols from TradingSolutions are listed in Figure 64. It is convenient to trade when neural networks are behind the recommendations. The Figure 65 pictures the prediction based on linear multiple regression made with WinQSB. Trading signals projection would be similar to previous cases.

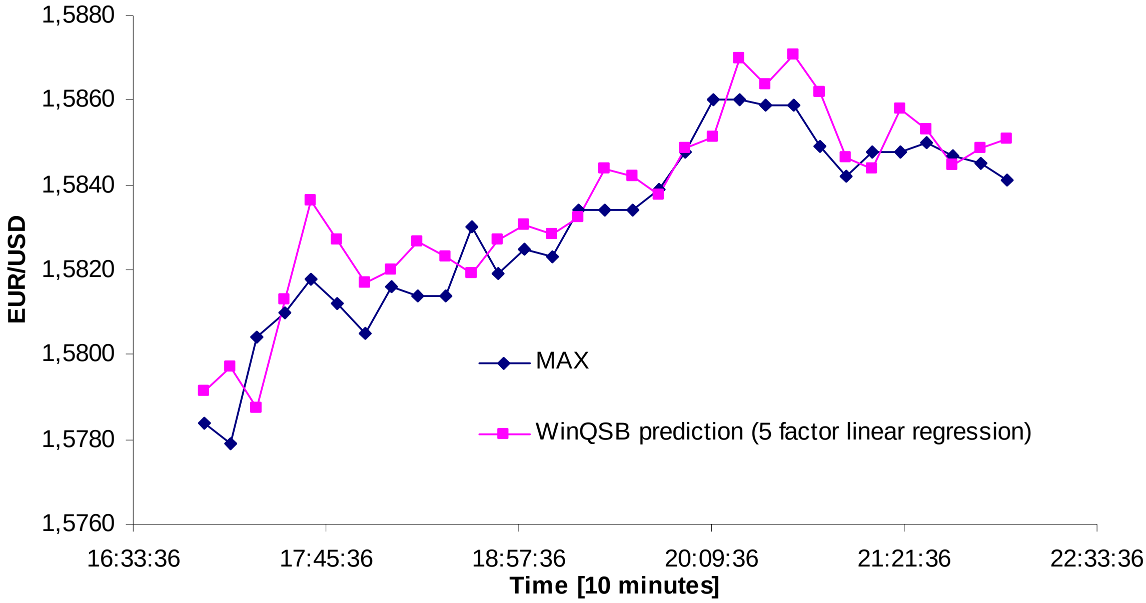


Fig. 65. WinQSB multiple regression – 10 minutes prediction

6.2 Appropriate Methods

I am nonprofessional, but I practically tried to figure out several advanced methods of economic analyses for prediction of exchange rates. From my point of view, neural networks performed best and I see the future in algorithmic trading, which means the use of artificial intelligence and computers to beat the market. I have read somewhere that about 18 000 price movements are made every trading day on the forex market. No human is able to absorb complete information about factors and variables that affect the market. Only complex systems of artificial intelligence are able to process thousands of real time data properly.

The second appropriate method is according to my opinion ARIMA, because it is quite accurate for short time prediction and its boundaries in figures are great. Then multiply linear regression seems also very hopefully.

I would not recommend using GARCH (too complicated) and linear regression in Excel.

6.3 Recommended Software

Small firm like Intense Capital, LLC can not afford to buy expensive software. However, there are also some applications that are free of charge. For example, WinQSB, which is the first software I would recommend. The firm already owns Microsoft Office Excel for data processing.

Tab. 8. Own rating of software: 10 - best, 1- worst

Software	**Price**	**Rating**
Microsoft Office 2007	400 USD	3
GARCH Toolbox (+ Optimization and Statistical Toolbox)	5 600 USD	5
WinQSB Forecasting and Linear Regression 2.0	free	6
NeuroSolutions for MATLAB	795 USD	7
Mathematica 5.2	3600 USD	7
Matlab	3 500 USD	8
Neural Network Toolbox (MATLAB)	1 900 USD	8
NeuroSolutions 5 level Consultants	1295 USD	8
NeuroSolutions for Excel (requires NeuroSolutions)	295 USD	8
TradingSolutions End-of-Day	995 USD	8
Statistica 7	1 500 USD	9
TradingSolutions Real-Time	1995 USD	9

The problem is how to obtain commercial software. Usually a demo version is available free of charge. Some functions are not accessible in demos. The trial versions, limited only in time, are a good way how to try software. Open source programs are alternative to commercial.

The criterion of no or low cost is not the only one purpose of software evaluation. The accuracy of results and the simplicity in data processing are main points. Therefore I made Table 8 which is the chart of preferred software. Ideal would be TradingSolutions Real Time, but it is expensive and too complicated for a beginner. The trader from Intense Capital will need several weeks to understand the questions of prediction by using neural network. So finally the order of usable software would go from WinQSB (free of charge) to Matlab Neural Network Toolbox (free demo) through Statistica NN (demo) to some platform that supports NN in real action (purchased).

CONCLUSION

Aim of this master thesis was to explore the possibilities of using advanced methods of economic analyses for prediction of exchange rates in a small firm. Available software commonly used for statistic and econometric predictions was utilized together with a new approach in neural network forecasting.

I am satisfied that I gained a lot of practical knowledge about predictions and limits of modern technologies. However, limits are also in knowhow of traders who would like to make money with advanced techniques.

The thesis provides only basic review of possible attitudes towards prediction. I estimate that this was only a top of famous iceberg in water, which means, about 80% of disposable knowledge is still hidden in thick books, contemporary scientific articles and the newest versions of software that still needs to be developed after this moment when I am writing these lines.

The practical contribution of my thesis will be seen after first dollars earned by neural networks in Intense Capital, LLC. The owner of the company currently tries to develop his own models with my little help, because his knowledge of practical trading is surely better than mine.

I would also recommend employing one more statistician in the firm who is able to provide the trader with appropriate models. According to my opinion, the financial modelling is as demanding and challenging as practical trading and if one person should develop a model in ten minutes and then trade under psychical pressure, it could not be good and healthy for him. The concentration and unflagging patience are major personal qualities of successful trader and also the user of neural networks and other advanced scientific techniques.

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LIST OF ABBREVIATIONS

ACF	Autocorrelation function
ANN	Artificial neural network
AR	Autoregressive, stochastic process
ARCH	Autoregressive conditional heteroscedasticity
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BIS	Bank for International Settlements
CFD	Contract for difference, a type of financial derivative
CSV	Comma-separated values, a file format
Forex, FX	Foreign exchange market
GARCH	Generalized autoregressive conditional heteroscedasticity
GATT	General Agreement on Tariffs and Trade
GDP	Gross domestic product
HLC	High-low-close chart
IMF	International Monetary Fund
LLC	Limited liability company
MA	Moving average
MAX	Maximum, high price
OHLC	Open-high-low-close chart
PACF	Partial autocorrelation function
PPP	Purchasing power parity
RMSE	Root mean square error
RS	Relative strength
RSI	Relative strength index

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APPENDICES

APPENDIX A I: SAXOTRADER 2 PLATFORM