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FINANCIAL MARKETS AND NON-LINEAR, DYNAMIC (DETERMINISTIC), CHAOTIC SYSTEMS

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Table of Content

Financial markets and Nonlinear-Dynamic (Deterministic) Chaotic Systems

Following I give a short overview over my forecast-strategy to forecast financial time-series.

First of all the bad news: I have no crystal ball!

And now the good news: all others don´t have a crystal ball, as well! Although:

I History

…in late 1994 we presented each Friday during some weeks one-week-forward-forecasts for the German 10 year Bond-Future and, the German Blue Chips and the S&P 500 Index at primetime at the German Broadcast TV 'NTV'. The interviews we gave and the forecasts we presented we made available to the audience for free. We stopped this project because our hit ratio reached 90%, not only in forecasting the correct direction but also reaching the predicted values, too and it was of course not sure, if we could keep such great results; for some it looked like we had a crystal ball! Of course: by far we had not!

Once in late 1995 Prof. Jochen Zschau [1][2], Professor for desaster research at the famous Telegraphenberg in Potsdam, came to me and my colleagues with a couple of shoe boxes containing 1,44 MB discs full of seismologic measurement data he collected before the Kobe Earthquake broke out. Prof. Zschau observed with his seismologic instruments, that there is an 'extensively silence', geographically. At that area where the 'silence' was concentrated most, later the earthquake broke out. He called the project to investigate this phenomenon 'Seismolab'. He had learned from us on TV. However, our company was at an early stage and we hadn´t the man-power, time and computers to involve us in such a forecasting project. It was a pity, but we had to focus on financial markets.

Before, in 1990/1991 last century I read an article of Mr. Dr. Francis Wong, Research Stuff Member of the Institute of Systems Science, National University of Singapore, with the title "Time series forecasting using back-propagation neural networks" [3]. That time I have had investigated, intensively already with adaptive algorithms like NN's for predicting financial markets and earlier in October 1987 I had an extraordinary experience with my 12-week-trend-predictions, I will tell you a little bit later.

Dr. Wong programmed an application called ‘Neuro-Forecaster’ which combined Chaos-Theory, Fuzzy Logic and Neural Networks with the target to sell it to banks. I was electrified by this program, because it was just what I needed those years. However, I missed a Genetic Algorithm, which could optimize several parameters of the NN like weighs and network topologies and others, automatically during the learning iterations, because a proper setting of parameters is time intensive and probably good results can only be reached by try and error. Dr. Wong told me, this wouldn´t be possible because it would be too time consuming to implement it in an already existing program and it would be time consuming to run a GA application on a 386 PC, as well. However, I insisted and after a while he agreed and implemented it into our PFC-Prediction System, PPS, which was based on his Neuro-Forecaster, labeled to our company. Later he implemented it into his ‘Neuro-Forecaster’, too.

More and more it became clear to me, that the financial markets are *non-linear, dynamic (sometimes deterministic) chaotic systems* like turbulences in the nature and that there must be other methods than the conventional once which have to be discovered. I guessed by myself, that Dr. Wong could be on the right track to analyse such complex systems like the financial markets are.

There had been many financial analysis programs for professional and private purposes on the market, but all of them couldn´t satisfy my needs. Can we become satisfied? Yes, we can! ;) I will try an approximation….

Parallel, in February 1995, I experimented with another analysis-software. Therefore I bought a highly sophisticated NN Software Library from the AND Corporation. This Software Library (DLL) has a unique characteristic and is under the Trade Mark of AND Corporation. In that early days AND Corporation sold their DLL Library. Later on, AND Corporation didn´t sell anymore their DLL Library. They just sell their services and consulting to big groups and banks up to now. Frequently they sell evaluation software, too, but this software is not open for programmers and the costs are around 200.000 $.

John Sutherland, the developer, calls it 'Holographic Neural Technology' [4]. Different to e.g. the common back-propagation NN's, this different type of cells provide their learn algorithms in complex numbers and vectors. A basic network which can convert to considerable learning results very fast, needs only four cells. A so called a) 'buffer cell', b) 'stat cell', c) 'cortex cell' and as input cell another 'buffer cell'. One could say, that within only one cell the total procedures of e.g. a back-propagation network (input, weight adjustments in the hidden layers and transformation to the output layer) are provided.

Everybody knows the first and second Gulf Wars. 1991 during the second Gulf-War, was a caesura in the military history. Patriot-Rockets have been launched against Saddam Hussein´s ballistic Scud-Rockets. Hussein tried to hit Jerusalem and Tel Aviv.

We remember: in the very beginning the Patriot-Rockets could not shut down the already flying ballistic Scud-Rockets, but during a short time period they became better and better and at least the Patriot-Rockets could shut down almost all Saddam Scud-Rockets.

What happened: the top of the Patriot-Rockets have been equipped first with the so called Kalman-Filter, developed by Rudolph E. Kalman, a statistical technique in electrical engineering, which was optimized to detect fast targets. Kalman was a scholar of Lotfi Zadeh, the inventor of FL. A bit later they have been equipped partial with John Sutherlands NN’s with its ‘Holographic Neural Technology’. The software in the beginning was trained to shut down fighters but no rockets. That’s why the Patriot-Rockets needed a few attempts to adapt to the new challenge to shut down rockets.

Only the head of each rocket with the neural adaptive software cost approximately 1 Mio. $.

I thought by myself, what is good for shooting down Scud-Rockets is good for analyzing financial markets, too. So I bought the complete DLL of Sutherlands ‘Holographic Neural Technology’ Professional System.

This is the impressive experience mentioned earlier, I don´t want to keep back: Some of us remember the ‘Black Monday’ at October 19th 1987. The Dow Jones fell 22.6 % within one day! In Australia the Stock Index fell 41.8 % and in Hong Kong even 45.8 % within one day, too! I remember one curious situation with my 12-Week ahead German-Dax-Index-forecasts that time, which I performed each week for 12 Weeks ahead. About 4 or 5 weeks before the ‘Black Monday’ (I don´t remember exactly) my forecast results have been conflicting. The 12-Week high forecasts showed permanently lower quotes over the 12-Week forecast horizon than the 12-Week low forecasts. Even though we controlled all settings, parameters and other adjustable components of our system over and over again, we could not figure out the reason, for this contradiction which made no sense. There could have been some hidden patterns in my indicators which had been able to anticipate this dramatic developments at the world stock exchanges.

Because of this strange results, which made no sense, I pleased my customers to be not invested. What a ‘luck’ for them, or was it no luck, probably?! This experience was an incentive to accelerate my efforts in finding an adequate systematic to analyze financial markets and to perform forecasts on time series. And like bedeviled, on Friday 13th in October 1989 the same phenomenon repeated, when the German-Dax-Index fell on the following Monday 12.8 % on one day. The forecasted 12-week highs computed by my systems rated under the computed 12-week low forecasts two weeks before that crash. That time the situation before the crash was different to October 1987:

It became known, that the take-over negotiations of the American Airline were off without results and the market participants feared, that other takeover negotiations could fail, as well because of poor willingness of banks to finance take-overs in general. On the ‘Black Monday’ 1987 there was no such a single reason for the disaster on the stock exchanges all over the world; that one was caused by the sum of different causes, which triggered this crash.

What is the difference of my strategy to common analysis methods? In the following I will give you just a brief overview!

Different to common analysis methods like chart techniques, and others like moving averages, or calculating momentum, relative strength and so on, I don´t use analytic tools, which are derivatives. I combine Chaos Theory, Fuzzy Logic, Neural Networks and Genetic Algorithms to a hybrid analysis system for detecting hidden patterns in a given time-series, associated to different other time-series, which are used as indicators for a determined target like the German Dax Index; I call them my four backbones. All the indicators are correlated in some way to the target, positive or negative, more or less strong. They are no derived calculations, like moving averages etc., they are themselves rough economic data, not smoothed, with outlying peeks included.

Even though smoothed data as indicators are much easier to process, I found out that this strategy is a good basis for trying to find hidden information, which can be helpful for performing time-series forecasts. Garbage in, garbage out: if we present smoothed and derived data-series as indicators to an analysis system, the system will not be able to find hidden patterns which could be used as basis for real forecasts. This means additionally, first: it is not enough to analyze the time-series itself, second: we have to correlate our target time-series with rough economic data like e.g. growth domestic products of different countries, currency-pairs, yields, employment-data….and so on and use them as input to the adaptive systems. Our success over years confirms this approach.

This procedure is necessary, because financial time-series and markets are not behaving linear, they are instead *non-linear, dynamic (sometimes deterministic) chaotic systems like a turbulences in the nature.*

I found out, that the only successful and substantial long lasting alternative is this combination of Chaos-Theory, Fuzzy Logic, Neural Networks and Genetic Algorithms for getting substantial forecast results. Chaos Theory for detecting, if a time-series is predictable itself by testing it with the Hurst Exponent, Fuzzy Logic to preprocess the data in so far as the data are not presented absolute, but relative to their environment, Neural Networks for learning non-linear data sets and try to generalize to the future and Genetic Algorithms to find the best parameter settings for the Neural Networks and the best Network structure, which performed best over a given time.

<u>II The first backbone is the Chaos-Theory</u> [5][6]

Example for a changing ***<u>deterministic</u>*** chaotic system to just a chaotic system, Geo 165

The financial markets are behaving like the smoke of a cigarette: As long as the smoke behaves as ‘calm’ column its developing direction and volume is calculable. This is possible during the system is *deterministic* (then it has memory or bias) and the Hurst Exponent is higher > or lower < 0.5. Higher than 0.5 means, that the recent trend is persistent, lower than 0.5 means, that the recent trend changes to the opposite. As soon as the system starts to diffuse into the space, the system changes to just chaotic. The Hurst Exponent oscillates around 0.5. Hurst was a British Hydrologist who lived 1880 to 1978. The same behavior like with the high-water levels we find in financial markets. Markets toggle always between *deterministic* and just *chaotic* conditions]. We have to take into account this fact with some ambitious effort!

The Hurst Exponent:

Its formula is a statistical measure, the 'Rescaled Range', of time series variability:

$$\mathrm{E}\left[\frac{R(n)}{S(n)}\right] = Cn^H \text{ as } n \to \infty ,$$

where

- $R(n)$ is the range of the first n values, and $S(n)$ is their standard deviation
- $\mathrm{E}[x]$ is the expected value
- n is the quantity in a time span of the observation period (number of data points in a time series)
- C is a constant.

How can Hurst help us to find hidden cycles and to know if a historical financial time series is random or if it has a memory, so we could extract a persistent or a changing trend in future?

Rescaled Range Analysis is an extension of Mandelbrot´s ‘range over standard deviation’ or ‘rescaled range’ analysis. It is a range of partial sums of deviations of time series from its mean, rescaled by its standard deviation.

<u>Definition of Rescaled Range:</u>

Given is an existing time-series t, with u observations:

$$X_{t,N} = \sum_{u=1}^{t} (e_u - M_N)$$

where

- X_{tN} *= cumulative deviation over N periods*
- e_u *= influx in year u*
- M_N *= average* e_u *over N periods*

The range then becomes the difference between the maximum and minimum levels attained above:

$$\boldsymbol{R=Max(X_{t,N})-Min(X_{t,N})}$$

where

- *R = range of Xx*
- *Max(X) = maximum value of X*
- *Min(X) = minimum value of X*

This range is divided by the standard deviation of the original observations, this 'rescaled range' should increase with time:

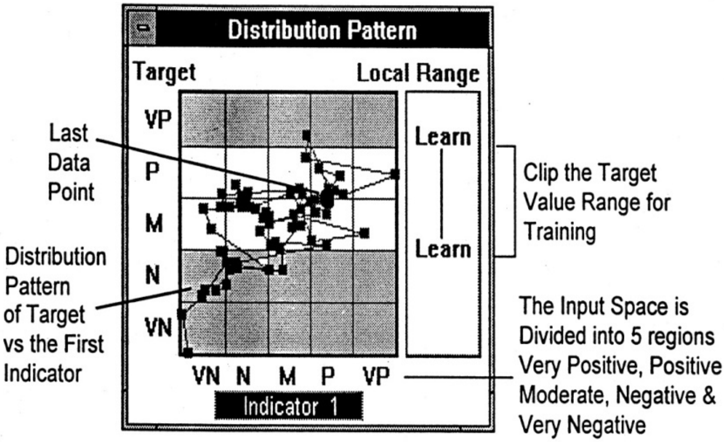
$$\boldsymbol{R/S = (a*N)^H}$$

where

- *R/S = rescaled range*
- *N = number of observations*
- *A = a constant*
- *H = Hurst exponent*

H equals 0.5 if the time series is random walk.

III The second backbone is Fuzzy Logic[7][8]



Presentation of the Indicator 1 to the NN as distribution from very positive (VP) to very negative (VN), PFC Prediction Systems (PPS)

The most important key aspect in the hybrid system is how the data are being presented to the NN. The challenge is, to reveal important relationships between the indicators and the target (desired values). It is not so important how many data are used, but how they are distributed.

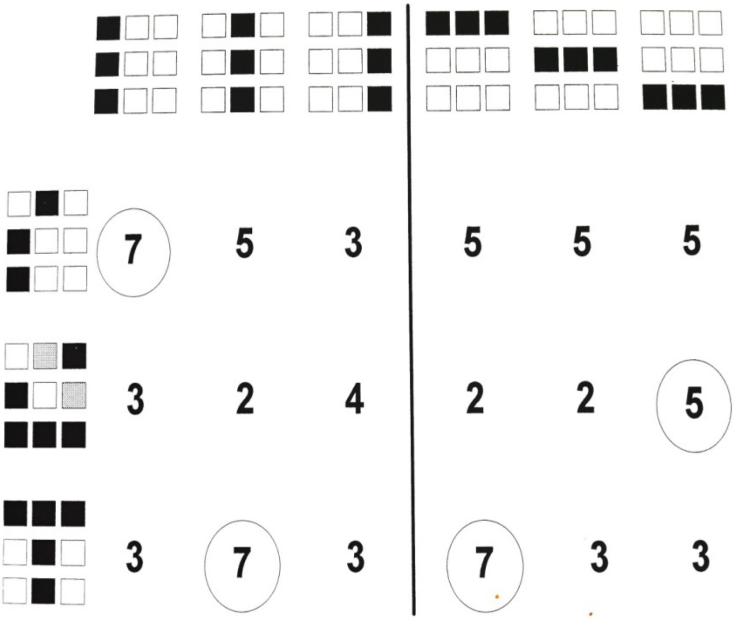
In the pre-processing I organize the data within a 'Fuzzy Matrix'. The input space is divided in 5 regions: very positive, positive, medium, negative, very negative. Each data point represents a fuzzy rule (membership function) which describes a rule between the indicator and the target, automatically. The advantage is, that no subjective grading of experts is necessary to formulate rules.

With this ‘distribution patterns’ it is easy to inspect, whether the input data are correlated to the target and in which scale they are represented and if there are enough representative data chosen.

I plotted a given indicator 1 (the indicators cannot be named in detail because of business confidentiality). Each of its data points is related to the desired target value points (the time series) and correlated from very positive (VP) to very negative (VN).

<u>IV The third backbone is the Neural Network</u> [3][13]

The core advantage of Neural Networks is their ability to generalize.

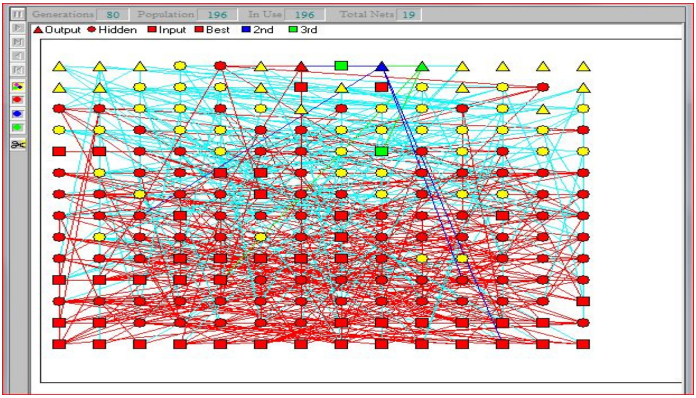


The principle of maximal similarity

Assumed the top left three square patterns mean ‘yes’, the market increases (+1) and the top right three square patterns mean ‘no’, the market declines (-1). During a couple of learning and testing iterations, the network learns this patterns, associates them with their particular mean and stores it in a, let me say, knowledge matrix. But what happens once it gets shown new unknown patterns?

It just ‘counts’ the similarities. In our example there is a similarity score of 7 with the three left learned patterns with the (top) left vertical new pattern, verdict: ‘yes, the market increases !’ 5 similarity scores are computed in the right learned pattern with the (middle) left vertical new pattern, verdict: ‘no, the market decreases!’ The last similarity score results are 7 for ‘Yes’ and 7 for ‘No’. The verdict: ‘don’t know!’

V The fourth backbone is the Genetic Algorithm [9]



Neural Network which learned best (red connections)

The automatically stored best detected Neural Network by a Genetic Algorithm keeps the best weights of neurons, PFC Prediction Systems (PPS)

Genetic Algorithms can optimize several parameters of the NN like weighs and network topologies and others, automatically during the learning iterations, because a proper setting of parameters is time intensive and probably good results can only reached by try and error without involving Genetic Algorithms.

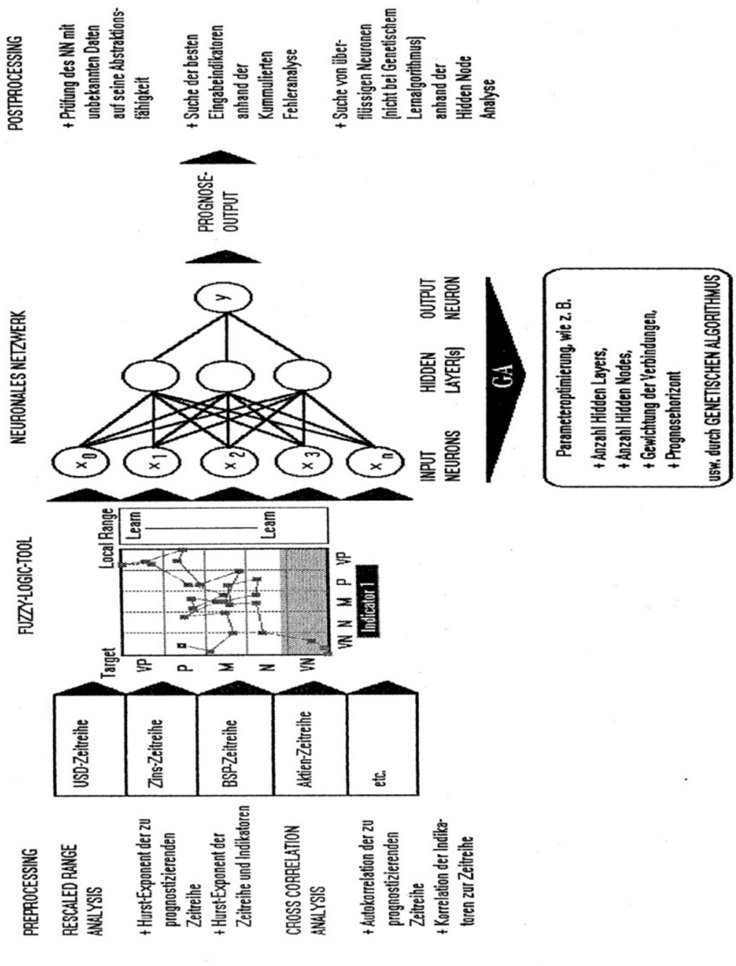
We all know, that political developments and economic changes can appear suddenly and can influence and drive the markets. How can we take account of this impact within our analyzed data basis? In so far as each political and economic development finds expression in all the rough economic data which we use as not smoothed indicators, we can be sure, that our analysis tools get this information, indirectly.

Another important practice is, that in cases of performing a couple of days, weeks or month ahead forecasts, I don´t just make for example a 12-month forecast, wait and after 12 month I calculate the next 12-month forecasts, no, I calculate each month a new 12-month forecast with a new database, so the data-knowledge-matrix will be destroyed each month and will be build new, each month. Like this I can be sure, that for instance a hidden fraction in the structure of correlations can be detected by our systems just in time and it can react to it, quickly. Sure, it is time intensive, but it helps to get good hitting quotes.

On the next page, I display a summary of the processing schema I use, which works successfully, since 1990.

Algorithms programming details and the list of used indicators are being not unveiled, due to company confidentialities.

VI Hybrid System [3][9][10][11][12]



Processing schema

VII Results

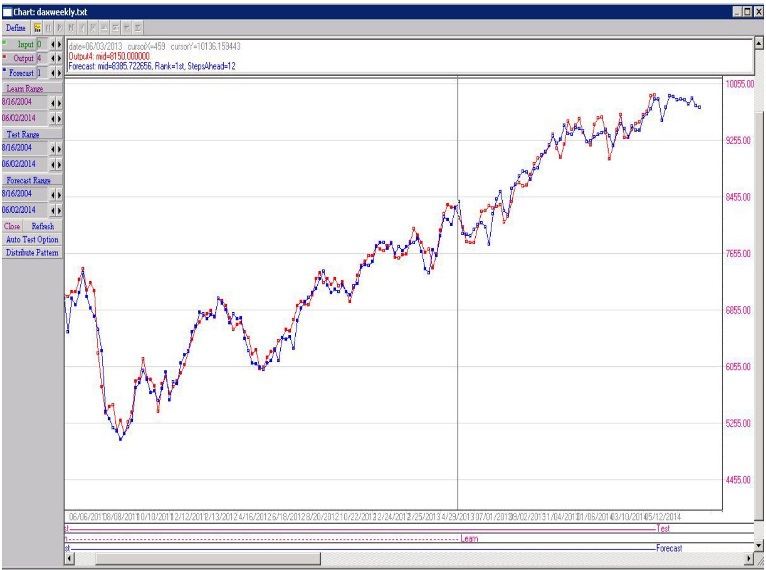
I chose exemplarily how my analysis system works on the German Dax Index on a weekly basis and on the German Bond Future on a monthly basis. Both with 12 weeks ahead respectively 12 month ahead forecasts.

In the case of the German Dax Index I will choose the following data set:

The set was trained on a weekly basis of the German DAX-Index from 2004.08.16 to 2013.06.2 (512 weeks which equal approximately 10 years) and the validation time of not learned data is from June 2013 to June 2014 (one year). This time range I chose, because that time, on June 2004, each analyst faced the question, if the already long lasting positive market trend will persist or if the market will reverse.

My example reveals, how my system handles such ambitious questions and tasks. I will explain step by step the complete process from pre-processing up to the post-processing procedures in this challenge.

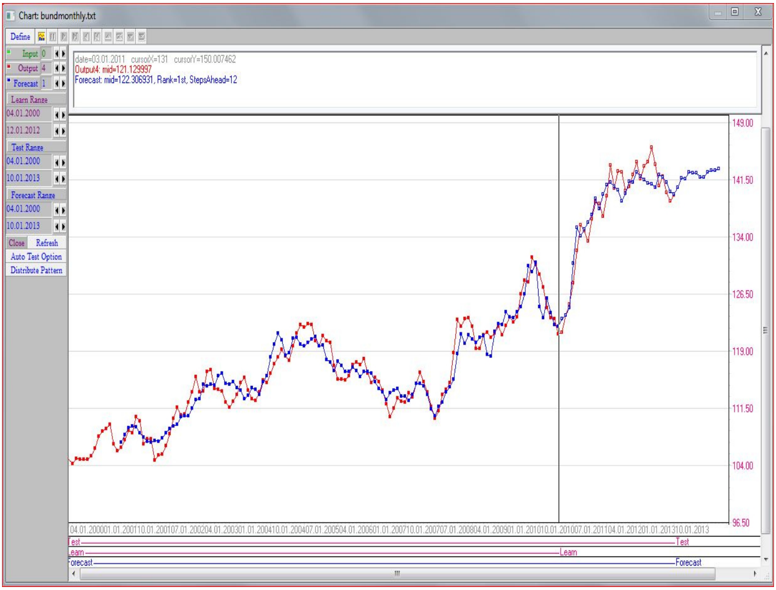
The result after different procedures is nothing to sneeze at. The system could generalize to the future data (future for the system, the validation set) from June 2013 to June 2014 (data points following the vertical line), after it had learned the data set from 2004.08.16 to 2013.06.03, using the four best indicators. The last further 12 blue data points show the forecast for the next 12 weeks.



Forecast of the German Dax Index on a weekly basis from June 2013 to June 2014

For the other example, the forecast of the German Bond Future on a monthly basis, I chose the following data set:

The application learns the data set, associated to the German Bond-Future, from 1.5.2000 to 1.4.2011, together with (initially) 30 raw economic indicators until 1.4.2011 (the indicators cannot be named in detail because of business confidentiality). Each third month is excluded from learning and taken already for verifying the generalizing abilities of the current network configuration. The remaining time range from 2011.04.02 to 2013.01.10 I choose as validating set because this market range shows a significant change in the direction. If the system forecasts this unknown range properly, I can trust it has learned hidden patterns in the training set. The last learning point will be 2011.01.04.



Forecast of the German Bond-Future on a monthly basis from April 2011 to January 2013

With this both examples I will explain exemplarily, how powerful and effective it can be, if we combine Chaos Theory, Fuzzy Logic, Neural Networks and Genetic Algorithms to forecast time series in the financial markets, independent of the underlying time step and forecast horizons.

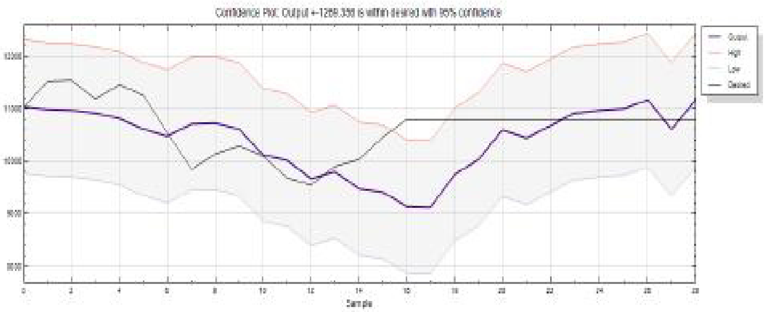
VIII Outlook

With the recommended method we are not anymore ‘victims’ of random unpredictable time series, so that we must ask just charts in our desperation what will happen in the near, middle and far future.

In the future I will investigate a very exciting challenge:

I will try to predict reliably, confidence ranges of given time-series over a given forecast horizon, within the market should continue to move with a given confidence-level of for example 95 %, not be confused with the mathematic probability calculation.

On the following page we can see a Confidence-Range of the German Dax Index 12 Weeks ahead:



Confidence-Range Prediction of the German Dax Index 12 weeks ahead

This example shows a confidence-range where the underlying data are week-end values of the German Dax-Index. The prediction begins, where the grey line moves just horizontal, 12 weeks ahead. Not everything is done, yet.

However, there are promising outcomes, already and I am sure that this analysis will be successful soon and help analysts to “navigate through the markets”. They can buy if the market approaches the low forecast range-line and sell if it approaches the high forecast range-line.

If I can perform this task reliable and stable, I can apply a trading system for customers.
It is always good to know today, what will be tomorrow ;)

IX Empirical findings

Elaboration of a hybrid system to forecast time-series for financial markets

That I am working with a hybrid system like described, is the basic realization this dissertation contributes. There are different basic approaches where some developers provide hybrid systems with their software, e.g. Ward Systems, USA, but not in my manner.
Chaos-Theory itself alone is insufficient for my demands, where I have to forecast financial markets which are changing all the time there conditions and environments. With chaos-theory it is possible to find long-lasting and persisting cycles to get an overall assertion, if a time series has bias or not. Before I start trying to predict any time-series, I ‘ask’ the chaos-theory if this time-series has bias or if it is random per se. If it is clear, that the time-series is just random, why should I take the efforts trying to predict it ?!
Fuzzy Logic itself alone is insufficient for my demands, too, because the data cloud with all its dynamic correlations which are not stable and change permanently, does not allow to formulate persistent valid rules which fuzzy logic transforms to membership functions. If one could formulate persistent valid rules, one could build fuzzy chips which are implemented in many technical applications, with all this rules. However, I use fuzzy logic just to present the indicator-values relative to the values of the forecasted time-series.

A Neural Network itself alone is insufficient for my demands, because to find the optimal parameter settings and network topologies is a Sisyphean task, never-ending ! There are infinite options to choose different network parameters like learning rates, different network types, learn tolerances, number of initial neurons or allowed average errors etc. All this leads to try and error and one can´t be sure, if one has the best setup for the given task.
With Genetic Algorithms one can solve complex optimization and classification problems, which are admittedly very complex, but cohere.
Additionally a classification is no forecast, due to the missing time parameter. Financial markets are not cohere and can´t be classified when all is said and done. This is the reason, why I use GAs to optimize the parameter settings of the neural network (within a given search space) and the network topology during the learning-iterations automatically. Not e.g. common NN transformations like sigmoid alone are applied, but GA algorithms.

Presentation of Indicator-Target-Relations applying Fuzzy Logic

To just analyze a single time-series without considering the influence of political and economic ‘environment’, is not sufficient. The ‘environment’ influences and drives the direction of the time-series more or less. So this influences must be considered. Substantial and political influences can be processed in so far easily, as this events are manifesting itself in the values of the indicators,

sometimes more sometimes less, sometimes substantial and sometimes only for short time periods.
Additionally I take into account, that my systems pre-processes the data which are handed over to the NN by shifting them through a ‘fuzzy-matrix’. Like this, the NN gets no absolute values but relative (fuzzyfied) values.

Elaborating how to find 'leading' and to reject 'lagging' indicators

One could assume: the more data the analysis system gets presented, the better it is. This is not the case. The question is, if good indicators can be presented to the system, where good indicators would be leading indicators and not lagging the time-series. Exemplarily I mention two indicators, one which is lagging and the other which is leading. More I cannot list, due to business confidentiality. The moving average is an example for a lagging indicator: it lags, because it is calculated by generating an average over a given number of time steps. The copper world price is an example for a leading indicator for stock markets. Copper is used in many industries to produce their products. The more this commodity is demanded, the more one can estimate, that the economy accelerates. This is indeed a fact over years and matches my observations and experience.
My analysis software is in so far very comfortable, as it detects itself automatically, if an indicator is leading or lagging. So even if I present the system a

couple of lagging indicators, I have tools to detect them very fast and I can disable them.

<u>Elaborating why all network parameters and weighs must be deleted and the procedure must be started each time new</u>

One outcome after years of investigating is, that it is necessary to delete all parameter settings, network-topologies and weighs. For each single forecast a new neural network must be set up. One could think, that once one has found a very good generalizing NN, that it can be saved and that it can be taken as basis for future forecasts in the same market. This is wrong. Earlier or later one will fail. Some keep their network-topology and parameter settings and 're-learn' with this parameters the NN with new data.

This is unrewarding, too, because the experience teaches, that due to the market dynamics the architecture of the analysis system must be adapted, permanently. If it is summer we wear different clothes than in winter! This is the same with dynamic market conditions und environments. It is always like this: Current economic information could change substantially and suddenly, so I must give the NN the 'chance' to learn such potential new information for considering them for the next forecast. This means: in the case that I perform 12-month-forecasts, I make each following month a new 12-month-forecast! It's the only way to get good forecast results. The average performance of the discussed method in this thesis is 71 % to 75 %

in forecasting the direction of a market, depending on the underlying time steps, Days, Weeks or Months! This principle provides a big part of this quality.
One can imagine, that if one starts the complete procedure for each single forecast, the computational effort is tremendous and time consuming, what is indeed true. However, if we could detect a few good indicators which are suitable to make forecasts, the system is able to handle this task quite fast.

Pointing up why indicators should be raw data

To take only raw, not smoothed and/or derived data as indicators, is another very important realizations during the years.
As described it is important to present to the system ‘good’ indicators. It seems attractive to smooth out peaks and outlying data in the time-series, because with peaks and outlying data points the system cannot learn correlations, there are no correlations. My system detects such peaks automatically and throws out such values as inputs during the learning iterations IF they are not useful. But, who knows if a peak carries important information for the given task? My system classifies it by comparing this data point with other data points of other indicators at the same point in time. If other indicators show similar peaks at the same point in time, it could be that such an outbreak is important and the system observes it.

‘Garbage in garbage out’: if we would use only smoothed data series, the forecast system had not a chance to detect hidden information which could be important for qualitative valuable forecasts. Additionally: for forecasting time-series, the ‘window size’ (how many data are presented by each iteration, combined days, weeks or month) carries great weight. The bigger the window size, the more time relevant (dependent) information can be learned.

The described conditions are fine - tuned and interconnected, which is the conclusion during 30 years of experience. If one takes out only one of this conditions, the total forecast results can collapse to bad results.

X Contributions of the dissertation

1. Elaboration of a model to forecast financial markets – a hybrid system implementing chaos theory, fuzzy logic, neural network and genetic algorithms.

2. Elaboration of a system of indicators for pre-processing the data resulting in relative (fuzzyfied) values.

3. Applying an algorithm for detecting data peaks automatically and throwing corresponding values as inputs during learning iterations.

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