APPLICATIONS IN COMPUTATIONAL FINANCE WITH A FOCUS ON APPROXIMATION OF FINANCIAL TIME SERIES BY NEUROCOMPUTING

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Dedicated to Sarah and Luisa

ABSTRACT

My dissertation shows how neural networks can be used in order to achieve more accurate approximation as well as better decision making in financial markets. In order to study its approximation ability for computational finance, I perform different empirical investigations. First, neural networks are suitable for approximating price functions of assets. I present empirical results for pricing and hedging FX options. Second, the usage of neural computing for forecasting financial time series is investigated, where neural networks compete with traditional time series models. I show empirical studies about the maritime freight rates market and the Chinese FX market. Above all mentioned techniques remains the question of neuronal computing application in the financial industry. In a last step I thus propose the implementation and design of a financial decision support system with neural networks. Nevertheless, I also expose limitations and further research topics in the area of neural networks, which could improve applications in computational economics in the future.

KEYWORDS

Neural Network, Financial Time Series, Approximation, Forecasting

ZUSAMMENFASSUNG

Meine Dissertation zeigt, wie Neuronale Netze für eine bessere Entscheidungsfindung an den Finanzmärkten eingesetzt werden können. Um die Approximationsfähigkeit für den Einsatz in Computational Finance zu analysieren, habe ich verschiedene empirische Untersuchungen durchgeführt. Zunächst eignen sich Neuronale Netze für die Approximation der Preisfunktion von Assets. Ich zeige empirische Ergebnisse für die Preisfindung und Absicherung von FX-Optionen. Zweitens wird der Einsatz von Neural Computing für die Prognose finanzieller Zeitreihen untersucht, wo Neuronale Netze mit traditionellen Zeitreihenmodellen konkurrieren. Dazu zeige ich empirische Analysen über den maritimen Frachtratenmarkt und den chinesischen Devisenmarkt. Über allen erwähnten Techniken bleibt die Frage der Anwendung von Neural Computing in der Finanzmarktindustrie. Ich schlage daher in einem letzten Schritt die Umsetzung und das Design eines Financial Decision Support System mit Neuronalen Netzen vor. Dennoch stelle ich auch Einschränkungen und weitere Forschungsthemen für den Einsatz von Neural Computing vor, die Anwendungen im Bereich von Computational Economics in Zukunft verbessern könnten.

SCHLÜSSELWÖRTER

Neuronale Netze, Finanzzeitreihen, Approximation, Prognose

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ACRONYMS

ARIMA	Autoregressive Integrated Moving Average.
ATM	at-the-money.
BAW	Barone-Adesi and Whaley.
BS	Black-Scholes.
CME	Chicago Mercantile Exchange.
CNH	offshore Yuan.
CNY	onshore Yuan.
CPU	Central Processing Unit.
DSS	Decision Support System.
FAUN	Fast Approximation with Universal Neural Networks.
FFA	Forward Freight Agreement.
FX	Foreign exchange.
GARCH	Generalized Autoregresssive Conditional Heterocedasticity.
GPU	Graphics Processing Unit.
HFT	High-frequency Trading.
ITM	in-the-money.
MLP	Multilayer perceptron.
NN	Neural Networks.
OTM	out-of-the-money.
RMB	Renminbi.
RMSE	root mean square error metric.

RW	Random Walk.
S&P	Standard Poor's.
SPI	Australian Share Price Index futures.
VAR	Vector Autoregression.
VECM	Vector Error Correction Model.
VLSI	Very-large-scale-integrated technology.

SYMBOLS

b	Bias.
C_t	Option call price at time t.
$C(I_n)$	Space of continuous functions on the n-dimensional unit hypercube $[0,1]^n$.
Δ	Option Delta.
ε	Error.
F_t	Forward/Futures price at time t.
$f(\cdot)$	Target function.
$\hat{f}(\cdot)$	Approximated network function.
Γ	Option Gamma.
k	Training pattern.
κ_{T-t}	Costs of carrying rate between period t and T.
$\varphi(\cdot)$	Network activation function.
r	Risk-free interest rate.
ρ	Performance metric.
S_t	Spot market price at time t.
σ	Volatility of the underlying.
τ	Maturity time $T-t$.
Θ	Option Theta.
w_j	Network weights from input to hidden layers.
ν_j	Network weights from hidden to output layers.
X	Strike price.
x	Network input variables.

PUBLICATIONS

I have grouped all papers by "publication classes". You will also find a list of all conferences where I have lectured.

JOURNAL PAPERS AND BOOK CHAPTERS

- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2013). *Numerical Approximation of Option Pricing Functions and Its Partial Derivatives by Neural Networks*. In: Dunis, C., Mettenheim, H.-J.v. and McGroarty, F. (Eds.), *New Developments in Quantitative Trading and Investment* (submitted/forthcoming). Palgrave Macmillan, Basingstoke.
- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2014). *Real-time Pricing and Hedging of Options on Currency Futures with Artificial Neural Networks*. Journal of Forecasting **33** (6), 419-432.
- Spreckelsen, C.v. , Kunze, F. , Windels, T. and Mettenheim, H.-J.v. (2014). *Forecasting Renminbi Quotes in the Revised Chinese FX Market - Can We get Implications for the Onshore/Offshore Spread-Behaviour?* International Journal of Economic Policy in Emerging Economies **7** (1), 66-76.

  Paper also presented at the 20th Forecasting Financial Markets Conference 2013, Hannover, Germany, May 29-31, 2013.
- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2014). *Steps towards a High-frequency Financial Decision Support System to Pricing Options on Currency Futures with Neural Networks*. International Journal of Applied Decision Sciences **7** (3), 223-238.

CONFERENCE CONTRIBUTIONS AND PROCEEDINGS

- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2013). *Pricing and Forecasting of High-Frequency Options on Currency Futures with Fast Neural Networks.* Paper presented at the 20th Forecasting Financial Markets Conference 2013, Hannover, Germany, May 29-31, 2013.

  Paper also presented at the 26th European Conference on Operational Research 2013, Rome, Italy, July 01-04, 2013.

- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2012). *Freight Rates in the Tanker Shipping Market - Short-Term Forecasting of Spot Rates and Derivatives with Linear and Non-Linear Methods.* Paper presented at the 19th Annual Meeting of the German Finance Association (DGF), Hannover, Germany, October 05-06, 2012.
- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2012). *Short-Term Trading Performance of Spot Freight Rates and Derivatives in the Tanker Shipping Market: Do Neural Networks provide suitable results?* In: Engineering Applications of Neural Networks, 13th International Conference, EANN 2012, London, UK, September 20-23, 2012. Communications in Computer and Information Science Volume 311, pp. 443-452.
- Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2012). *Spot and freight rate futures in the tanker shipping market: short-term forecasting with linear and non-linear methods.* In: Operations Research Proceedings 2012: Selected Papers of the International Annual Conference of the German Operations Research Society (GOR), Leibniz University of Hannover, Germany, September 5-7, 2012, pp. 247-252.

REPORTS

- Spreckelsen, C.v. , Bartels, P. and Breitner, M.H. (2006). *Geschäftsprozessorientierte Analyse und Bewertung der Potentiale des Nomadic Computing.* IWI Discussion Paper No. 17, 14. Dezember 2006.

PRESENTATIONS AT CONFERENCES

- International Annual Conference of the German Operations Research Society (GOR), Hannover, Germany, September 5-7, 2012.
- 13th International Conference, EANN 2012, London, UK, September 20-23, 2012.
- 19th Annual Meeting of the German Finance Association (DGF), Hannover, Germany, October 5-6, 2012.
- 20th Forecasting Financial Markets Conference 2013, Hannover, Germany, May 29-31, 2013.
- 26th European Conference on Operational Research 2013, Rome, Italy, July 01-04, 2013.

				Rankings		
Chapter	Date	Title	Entity	VHB[a]	SJR[b]	ABDC[c]
A	forthcoming	The »Greeks Approximation« Paper: Numerical Approximation of Option Pricing Functions and Its Partial Derivatives by Neural Networks	Book Chapter			
B	2014	The »Pricing and Hedging Options« Paper: Real-time Pricing and Hedging of Options on Currency Futures with Artificial Neural Networks	Journal	B	Q2	A
C	2014	The »Forecasting Renminbi Quotes« Paper: Forecasting Renminbi Quotes in the Revised Chinese FX Market - Can We get Implications for the Onshore/Offshore Spread-Behaviour?	Journal		Q4	C
D	2014	The »Financial Decision Support System« Paper: Steps towards a High-frequency Financial Decision Support System to Pricing Options on Currency Futures with Neural Networks	Journal		Q2	
E	2013	The »Pricing Options« Paper: Pricing and Forecasting of High-Frequency Options on Currency Futures with Fast Neural Networks	Conference			
F	2012	The »Forecasting Freight Rates I« Paper: Freight Rates in the Tanker Shipping Market - Short-Term Forecasting of Spot Rates and Derivatives with Linear and Non-Linear Methods	Conference			
G	2012	The »Trading Tanker Freight Rates« Paper: Short-Term Trading Performance of Spot Freight Rates and Derivatives in the Tanker Shipping Market: Do Neural Networks provide suitable results?	Proceeding			
H	2012	The »Forecasting Freight Rates II« Paper: Spot and freight rate futures in the tanker shipping market: short-term forecasting with linear and non-linear methods	Proceeding			
J	2006	The »Nomadic Computing Paper« Paper: Geschäftsprozessorientierte Analyse und Bewertung der Potentiale des Nomadic Computing	Report			

[a] Verband der Hochschullehrer für Betriebswirtschaft e.V. 2.1.
[b] SCImago Journal Rank (SJR indicator).
[c] Australian Business Deans Council Journal Quality List 2013 Review.

EXECUTIVE SUMMARY

Estimating an underlying relationship from a given finite input-output data set - or more precisely: function approximation involves - has been the fundamental problem for a variety of applications in financial engineering. Nowadays, feedforward neural networks such as Multilayer perceptron (MLP) have been widely used as an alternative approach to function approximation since they provide a generic functional representation. They have been shown to be capable of approximating any continuous function with arbitrary accuracy.

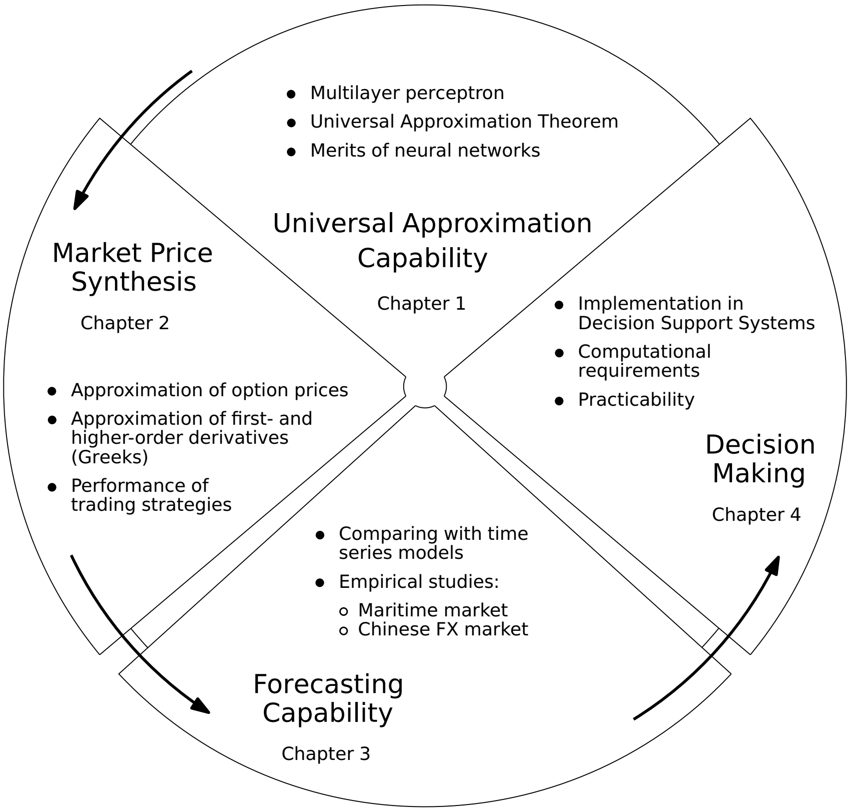
This dissertation shows how neural networks can be used in order to achieve more accurate approximation as well as better decision making in financial markets. The importance of better market price approximation or synthesis, forecasting, and the relationship between spot and derivative markets for better decision making, in the light of increasing financial market volatility and internationalized capital flows, cannot be over exaggerated. In order to study its approximation ability for computational economics, I perform different empirical investigations. Figure 0.1 summarizes the organization of my dissertation.

NETWOK APPROXIMATION BY THEORY

The universal approximation theorem of Cybenko (1989) and Hornik (1989) provides the latent basis of my empirical studies. Artificial neural networks can be mathematically shown to be universal function approximators. This means that NNs can automatically approximate whatever functional form characterizes the data best. Since it is my goal to extract an alternative option pricing function by market observations, I focus on MLP that are applicable to non-linear regression problems. I follow the argumentation of Hornik (1989), that feedforward networks with only one hidden layer and a linear output unit are able to approximate simultaneously its unknown derivatives up to an arbitrary degree of accuracy. This characteristic is substantial since the partial derivatives of a pricing formula are needed for the hedging of option positions.

I perform my network training with the Fast Approximation with Universal Neural Networks (FAUN) neurosimulator. As described in Mettenheim and Breitner (2010) two reasons make FAUN suitable for HFT. First, the FAUN neurosimulator uses fine-grained parallelization. This allows easily achieved speedups on dual and quad core CPUs. FAUN also features coarse-grained parallelization using an easy to install grid computing client. It is possible to use clusters of heterogeneous workstations. Second, using reverse accumulation and matrix algorithms allow a very efficient computation.

Figure 0.1: Overview



MARKET PRICE SYNTHESIS

Neural networks are information processing tools commonly used for function approximation and classification. They offer an alternative way of developing option pricing and hedging models. Their particular strength lies in their ability to approximate highly non-linear and multivariate relationships without the restrictive assumptions implicit in parametric approaches. This property of neural networks makes them attractive for problems such as pricing and hedging options. Moreover, they are adaptive and respond to structural changes in the financial markets. The drawback of this approach is that it is highly data driven, requiring large quantities of historical prices.

I present empirical results for pricing and hedging FX options. The empirical results confirm the ability of neural networks for universal approximation. Subsequent studies mostly investigated daily equity index options data for option pricing approximations. Despite the high liquidity of FX options markets, there is no noticeable investigation about pricing FX options with neural networks in a HFT-context.

Hence, I build on prior investigations, but I extend my studies paper B and paper E with a run-time trading process in order to uncover special characteristics of high-frequency data. In particular, I pose the following challenge: If option prices were truly determined by the theoretical model exactly, can the closed-form formula be estimated by learning networks with a sufficient degree of accuracy to be of practical use? Furthermore, can both models be implemented in an automatic HFT trading process, in which a signal must be precise enough to trigger trades in a fraction of a second?

To assess the approximation capability I use two big data sets. On the one hand there is a full high-frequency data set of cleared 118,291 quotes of an EUR/USD option on currency futures with various strike prices available. On the other hand I generate more than 20,000 simulated intra-day option prices to get a broader range of data.

To assess the potential value of network pricing formulas in HFT, I implement two different investigations: First, paper B and paper E perform a rolling 15 minutes out-of-sample interval for each trading day to assess the models pricing ability. The derived approximation function is then used to perform a delta-hedging examination. All results are benchmarked using a theoretical closed-form model for pricing options on futures. Second, in order to carry out the approximation capability of the network function and its partial derivatives the network in paper A trains on a simulated data set without any rolling-window technique in order to investigate the numerical approximation of option price functions and their derivatives. I am also interested in the question of whether the data availability is crucial for a better approximation.

FORECASTING CAPABILITY

The usage of neural computing for forecasting financial time series is investigated, where neural networks compete with conventional time series models. Theoretically, the efficient market hypothesis implies that in an efficient market, it is impossible to obtain better predictions using forecasting methods because the observable price already reflects all available information and price fluctuations that will occur in the future randomly. In reality, however, systematic patterns might be found in financial time series.

First, I show empirical studies about the maritime spot and derivatives freight rates market. In paper F, paper G and paper H I perform several forecasting techniques in order to examine the forecasting ability of freight rates. I find a lack of jointly spot and forward forecasting investigations with neural networks. Thus, I extend my study on freight derivatives and a wider range of time series models. The main objective of this paper is to investigate neural networks prediction ability for maritime business forecasting and provide a practical framework for actual forecasting and trading applications of neural computing.

I sample daily prices of the International Maritime Exchange (Imarex) TD3 and TD5 freight forward contracts. These contracts are written on daily spot rates for TD3 and TD5 published by the Baltic Exchange. The spot and Forward Freight Agreement (FFA) data is available from 5 April 2004 to 1 April 2011. I investigate short-term forecasts of spot and FFA prices in the market in order to make inferences about the efficiency and usefulness of FFA rates. The question arises: Are forward rates expectations of spot rates? I consider both univariate and multivariate model specifications fitted with lagged spot freight rates returns $\Delta\hat{S}_t$ and forward rates returns $\Delta\hat{F}_t$.

Another interesting research object is the very unique Chinese FX market, which exhibits a dual characteristic of the market. The uniqueness comes from the two separated markets for the Renminbi (RMB), namely the onshore Yuan (CNY) and offshore Yuan (CNH) market. The main goal of paper C is to gain insights in the comparatively new market for offshore RMB and to detect first indications for feasible forecasting models for the onshore RMB respectively to improve CNY spot forecasts. I employ a simple GARCH model as well as neural networks. I do also analyze the somewhat older NDF market for which Ding et al. (2012) found a strong relationship with the CNY spot rate. As their work deals with the three RMB markets until June 2011 and since then the CNH market grew quite rapidly and seems to be replacing the NDF market, I lay our main focus on the CNH market.

I collect daily exchange rate data for onshore spot CNY, offshore spot CNH, one-month offshore NDF and CNH forward rates from Bloomberg. The sample period spans 08 September 2010 to 20 March 2013. All forecast models are separated in univariate and multivariate classes: The univariate models consist of single series of CNY, CNH and their spread. I exclusively analyze the CNY in a multivariate way by incorporation of the one-month forward rates NDF and CNH respectively.

DECISION MAKING

Above all mentioned techniques remains the question of neuronal computing application in the financial industry. In a last step I thus propose the implementation and design of a financial decision support system with neural networks, which is a more business informatics oriented discussion. The merits of neural networks especially for high-dimensional problems are shown.

I present steps towards a model-driven DSS to pricing option on currency futures, which can be embedded in a high-frequency trading process. In order to develop an appropriate DSS, I use the design science methodology of Hevner et al. (2004). Efficient implementation of trading algorithms is crucial, because a vast amount of data has to be processed in very short time.

MAIN CONTRIBUTIONS

In summary, I have attempted to provide empirical evidence for neural networks capability to approximate financial time series. Main contributions are:

- Model option prices derived from NN can synthesize HFT option market prices in a similar manner, but in a simultaneous way and with a more parsimonious input specification. There is e.g. no need of volatility or interest estimation.

- If market liquidity exists, which is equivalent to full data availability in a particular state space, learning networks are capable to approximate first- and higher-order partial derivatives with a sufficient accuracy. But the approximation accuracy decreases with higher-order partial derivatives.
- However, I can not confirm the hypothesis that once a predominant network approximation is found for pricing purposes, the same could be applied for hedging. I have to notice that it is an exhausting balancing act for learning systems to apply the delivered pricing approximation function on unknown hedge parameters.
- In case of forecasting financial time series neural network results are comparable to those of the other models. Some regularities from two different financial markets:
- Tanker freight rates market: Changes in spot rates are explained by autocorrelation and by changes in the forward rates; but: changes in forward rates are not explained by past changes in spot rates. There is, however, a highly significant autocorrelation in forward rates that is difficult to conciliate with efficient markets. These results imply that the futures prices contain valuable information about future spot rates.
- Chinese FX market: Our results do not support our assumption of a parity between the CNY and CNH. On the one hand the fact that the used forecasting methods do not outperform the naïve RW forecasts points to the direction that the price movements in the Chinese FX markets are similar to the movements in developed economies' FX markets, which are said to be rather efficient. On the other hand I found strong evidence that structural breaks do exist in the RMB markets.
- Neural networks are a suitable core engine for a model-driven DSS embedded in a high-frequency trading process and can support trading decisions.

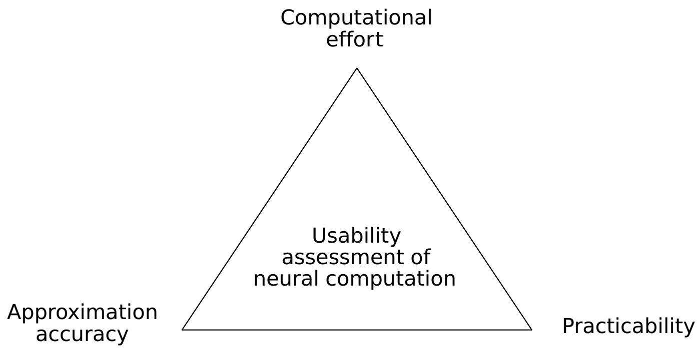
Hence, this dissertation provides empirical evidence that neural networks may be put to work for more accurate approximation and for better decision making in financial markets.

EVALUATION CRITERIA

In evaluating my empirical studies, there are still some questions left: First, can the empirical results be generalized? Second, are there any restrictions to a practical implementation, which have not been taken into account? For this purpose, I have identified three assessment criteria as shown in figure 0.2. I will give answers in detail to the two questions mentioned above in chapter 5.

In summary, it can be stated that:

Figure 0.2: Assessment criteria



- All empirical investigations in each case refer only to certain time periods and assets. There is a need for further evidence to confirm a generalization or robustness of the models.
- The approximation of neural networks suffer from inhomogeneous data density, in particular when trainable data is rare.
- To implement large and effective software neural networks, much processing and storage resources need to be committed. Neural network systems will often need to simulate the transmission of signals through many of these connections and their associated neurons - which must often be matched with incredible amounts of CPU processing power and time.

The good news are: I also expose further research topics in doing with neural networks, which could improve neural networks applications in computational economics in future.

Part I

A SURVEY AND CRITICAL REVIEW

The following part summarizes and evaluates main findings of my empirical research during my research on this dissertation. First, I give a brief introduction about the research field and methodology. Moreover, I discuss all appended papers in three major chapters before I discuss and conclude my dissertation.

1

INTRODUCTION

Science, my lad, is made up of mistakes,
but they are mistakes which it is useful to make,
because they lead little by little to the truth.

— Jules Verne, *A Journey to the Center of the Earth*

1.1 SYNTHESIS, FORECASTING AND DECISION MAKING

Function approximation, which finds the underlying relationship from a given finite input-output data is a fundamental problem in a vast majority of applications in computational economics, such as prediction, pattern recognition or data mining. Various methods have been developed to address this problem, where one of them is by using artificial Neural Networks (NN). The main idea in conventional approaches is to find a global function of systems based on mathematical tools. However, it is well known that these methods have been found to be unsatisfactory in coping with ill-defined and uncertain systems. In order to circumvent these problems, model-free approaches using neural networks have been proposed. Functionally, a neural network can be described as a function approximator. They aim at obtaining an approximation of an unknown mapping

$$f : \mathbb{R}^n \to \mathbb{R}^m$$

from sample patterns drawn from the function $f(\cdot)$. Artificial neural networks can be universal function approximators for even non-linear functions. They can also estimate piece-wise approximations of functions. This dissertation seeks to explore empirically these possibilities.

The importance of better market price approximation or synthesis, forecasting, and the relationship between spot and derivative markets for better decision making, in the light of increasing financial market volatility and internationalized capital flows, can not be over exaggerated.

Nowadays, the pricing of instruments for hedging positions on underlying risky assets and optimal portfolio diversification have become major activities in financial institutions. One of the key questions facing practitioners in financial markets is the market price synthesis of derivative products as a demand for these instruments grows. Correct pricing of risk, of course, crucially requires the use of models that give relatively accurate out-of-sample prices.

Market price synthesis provides the basis for another discipline: The prediction or forecasting of time series. Forecasting simply means understanding which variables lead or help to predict other variables, when many variables interact in volatile markets. This means looking at the past to see what variables are significant leading indicators of the behavior of other variables. It also means a better understanding of the timing of lead-lag relations among many variables, understanding the statistical significance of these lead-lag relationships, and learning which variables are the more important ones to watch as signals for further developments in other returns. Obviously, if one know the true underlying model generating the observable market data, one will know how to obtain the best forecasts. However, if the true underlying model may be too complex or unknown, one has to approximate the true underlying model by approximating models. Having in mind that approximation models exhibit model risk, neural network approaches will emerge as a strong competitor to the standard benchmark linear model.

The ability to forecast the future, based only on past data, leads to strategic advantages, which may be the key to success in financial institutions. In real life, one would be interested not only in efforts in forecasting, but also in practical trading strategies with possibility of taking positions in financial markets. Traders must predict asset price movements in order to sell at top range and to buy at bottom range. Decision making is the process of developing and analyzing alternatives, and then selecting from the available alternatives. Market price synthesis and forecasting are basic disciplines in the process of decision making. Hence, both disciplines are always connected with the decision support system to improve decision-making.

Financial problems, in particular, can be of an exceptionally complex and unstructured nature. The sophisticated mathematical financial models in use, the incredibly large, dynamic, rapidly expanding data sets involved, and the potential for catastrophic losses are factors that contribute to the increasingly important role of Decision Support System (DSS) in the finance. In some decision situations, quantitative models embedded in a DSS can help managers to make better decisions. Model-driven DSSs use algebraic, decision analytic, financial, simulation and optimization models to provide decision support. Real-time decision support systems are emerging due to the new development of artificial intelligence techniques such as machine learning or the improvement of computer hardware and mathematical programming techniques in terms of speed of CPU and the problem size. As the survey indicates, a large proportion of DSSs involves optimization systems. Ever increasing computing power makes it possible to solve a large scale mathematical optimization model in a fraction of a second. Moreover, the machine learning approach can obtain knowledge from prior data, decisions and examples, and contribute to the creation of DSS to support repetitive, complex real-time decision making.

The message of this dissertation is that financial decision makers now have the computational power and methods for more accurate diagnostics, forecasting, and control in volatile, increasingly complex environments at hand. Decision makers need no longer confine themselves to linear or log-linear models, or assume that underlying stochastic processes are Gaussian or normal in order to obtain forecasts and pinpoint risk-return trade-offs. In short, one can go beyond linearity and normality with the use of neural networks.

1.2 APPROXIMATION BY NEURAL COMPUTING

1.2.1 *Universal Approximation Theorem*

In the mathematical theory of neural networks, the universal approximation theorem states that a feed-forward network with a single hidden layer containing a finite number of neurons, the simplest form of the MLP, is a universal approximator among continuous functions on compact subsets of $\mathbb{R}^n$. This means that neural networks can automatically approximate whatever functional form best characterizes the data. While this property gives little value if the functional form is simple, it allows neural networks to extract more benefits from complex underlying functional forms.

One of the first versions of the theorem was proved by Cybenko (1989) for sigmoid activation functions. Hornik (1991) showed that it is not the specific choice of the activation function, but rather the multilayer feedforward architecture itself which gives neural networks the potential of being universal approximators.

I begin with some definitions of Hornik (1989) to speak precisely about the class of multi-layer feedforward networks under consideration. For notational convenience the results are only formulated for the case where there is only one hidden layer and one output unit.

Definition. Let $f(\cdot)$ be a continuous real-valued function on a compact subset U of $\mathbb{R}^n$, i.e.

$$\hat{f} : U \subset \mathbb{R}^n \rightarrow \mathbb{R} \text{ (or} : f \in C(U, \mathbb{R})). \tag{1.1}$$

A typical example of a compact subset would be the n-dimensional product of the unit interval $[0, 1]^n$.

The set $C(U, \mathbb{R})$ can be very large. Hence, one is interested to find a subclass K of functions, such that for any $\varepsilon > 0$ one can always find $\hat{f} \in K$ that $|f(\cdot) - \hat{f}(\cdot)| < \varepsilon$, where $| \cdot |$ represents some distance measure in $C(U, \mathbb{R})$.

K can be the set of neural nets with n input variables and one output. Given any $f(\cdot)$, and any $\varepsilon > 0$, the question follows, if one can always find a neural net $\hat{f}(\cdot)$ that approximates $f(\cdot)$, i.e.

$$\rho = \sup_{x \in U} |f(x) - \hat{f}(x)|, \tag{1.2}$$

where ρ denotes some performance metric. In other applications, one thinks of the inputs as random variables and are interested in the average performance where the average is taken with respect to the input environment measure μ, where $\mu(\mathbb{R}^n) < \infty$. In this case, closeness is measured by the $L^p(\mu)$ distances

$$\rho = \left[\int_{\mathbb{R}^n} |f(x) - \hat{f}(x)|^p d\mu(x) \right]^{1/p}. \tag{1.3}$$

The special case $p = 2$ corresponds to mean square error. The class of MLP networks can be defined as follows:

Definition. For any $n \in \mathbb{N}$, A^n is the set of all affine functions from $\mathbb{R}^n$ to $\mathbb{R}$, that is, the set of all functions of the form $A(x) = w \cdot x + b$ where w and x are vectors in $\mathbb{R}^n$ and $b \in \mathbb{R}$ is a scalar. In the present context, x corresponds to network input, w corresponds to network weights from input to the intermediate layer, and b corresponds to a bias.

A number of diverse application areas are concerned with the representation of general functions of an n-dimensional real variable, $x \in \mathbb{R}^n$, by finite linear combinations of the form

$$\sum_{j=1}^{N} v_j \varphi(w_j^{\mathsf{T}} x + b_j). \tag{1.4}$$

A leading case occurs when $\varphi(\cdot)$ is a sigmoidal function, in which case $\sum^n(\varphi)$ is the familiar class of output functions for single hidden layer feedforward networks with a sigmoid function at the hidden layer and no sigmoid function at the output layer. The scalars v_j, correspond to network weights from hidden to output layers.

Definition. A function $\varphi : \mathbb{R} \to [0, 1]$ is a sigmoidal function if it is non-decreasing, $\lim_{\lambda\to\infty} \varphi(\lambda) = 1$, and $\lim_{\lambda\to-\infty} \varphi(\lambda) = 0$. Because sigmoidal functions have at most countably many discontinuities, they are measurable.

Funahashi (1989) and Cybenko (1989) proofed the following

Theorem. *Let $\varphi(\cdot)$ be a nonconstant, bounded, and monotonically-increasing continuous function. Let I_n denote the n-dimensional unit hypercube $[0, 1]^n$. The space of continuous functions on I_n is denoted by $C(I_n)$. Then, given any function $f \in C(I_n)$ and $\varepsilon > 0$, there exist an integer N and real constants $v_j, b_j \in \mathbb{R}$, $w_j \in \mathbb{R}^n$, where $j = 1, \ldots, N$ such that one may define:*

$$\hat{f}(x) := \sum_{j=1}^{N} v_j \varphi(w_j^{\mathsf{T}} x + b_j) \tag{1.5}$$

as an approximate realization of the function f where f is independent of $\varphi(\cdot)$; that is,

$$|f(x) - \hat{f}(x)| < \varepsilon \tag{1.6}$$

for all $x \in I_n$. In other words, functions of the form $\hat{f}(x)$ are dense in $C(I_n)$.

Proof. Let $K \subset C(I_n)$ be the set of functions of the form $\varphi(x)$ as in equation 1.5. One claims that the closure of K is all of $C(I_n)$. Assume that the closure of K is not all of $C(I_n)$. Then the closure of K, say $\mathbb{R}$, is a closed proper subspace of $C(I_n)$. By the Hahn-Banach theorem, L is a bounded linear functional on $C(I_n)$. This bounded linear functional L is of the form

$$L(h) = \int_{I_n} h(x) d\mu(x) \tag{1.7}$$

for all $h \in C(I_n)$. In particular, since $\varphi(w^\top x + b)$ is in $\mathbb{R}$ for all w and b, we must have that

$$\int_{I_n} \varphi(w^\top x + b) d\mu(x) = 0 \tag{1.8}$$

for all w and b. However, assuming that $\varphi(\cdot)$ was discriminatory so that this condition implies that $\mu = 0$ contradicting the assumption. Hence, the subspace K must be dense in $C(I_n)$. □

If one thinks of the network architecture as a rule for computing values at m output units given values at n input units, hence implementing a class of mappings from $\mathbb{R}^n$ to $\mathbb{R}^m$, one can ask how well arbitrary mappings from $\mathbb{R}^n$ to $\mathbb{R}^m$ can be approximated by the network, in particular, if as many hidden units as required for internal representation and computation may be employed.

Moreover, in many applications, it is also necessary that the derivatives of the approximating function implemented by the network closely resemble those of the function to be approximated, up to some order. This issue was first taken up in Hornik et al. (1990), who discuss the sources of need of smooth functional approximation in more detail.

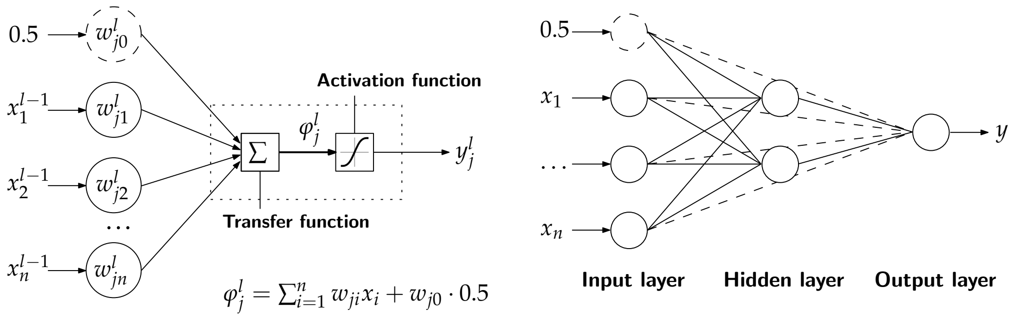
Similarly, Hornik (1989) established that whenever φ is continuous, bounded and nonconstant, then, for arbitrary compact subsets K of $\mathbb{R}^n$ standard multilayer feedforward networks with activation function $\varphi(\cdot)$ can approximate any continuous function on K arbitrarily well. Hence, he implied that "any lack of success in applications must arise from inadequate learning, insufficient numbers of hidden units or the lack of a deterministic relationship between input and target." The results establish that standard multilayer feedforward networks are capable of approximating any measurable function to any desired degree of accuracy, in a very specific and satisfying sense.

1.2.2 *Multilayer Feedforward Networks*

Neural networks are mathematical, algorithmic models inspired by biological artificial neural networks. They consist of basic units, termed neurons, who have predispositions that affect the strength of their output. The neuron combines the inputs, incorporates the effect of the bias, and outputs signals. In both real and artificial neurons, learning occurs and alters the strength of connections between the neurons and the biases.

Since it is my goal to extract an alternative option pricing function or predict any market observations, I focus on MLP that are applicable to non-linear regression problems. I follow the argumentation of Hornik (1989), that feedforward networks with only one hidden layer and a linear output unit are able to approximate simultaneously its unknown derivatives up to an arbitrary degree of accuracy. This characteristic is substantial since the partial derivatives of a pricing formula are needed for the hedging of option positions.

Figure 1.1: Exemplarily 3-layered perceptrons used in this dissertation



(a) Neuron

(b) Feedforward network

Note that FAUN set the bias $b = w_{j0} \cdot 0.5$.

Referring to figure 1.1, given an input $\vec{x}^{l-1}_i$ in layer $l-1$, a neuron j can compute an output y^l_j in layer l according to its prior training, represented by the weight vector $(w^l_{j0}, \vec{w}^{l\mathsf{T}}_j)^\mathsf{T}$ where superscript T denotes the transpose operation. The weights provide the abilities of prediction or classification to the system. Firstly, the inputs $(\vec{x}^{l-1}_i)$ fed to the input layer are weighted and summed up. Then they are entered to an activation function φ^l_j in order to get an output from each neuron in the hidden layer. The weights are iteratively changed until the best loads are obtained. To find the right weights within a so-called training process thousands of MLPs with various topologies and with different weight initializations are trained.

Once a set of discrete data is available, the neural network can be trained to approximate or generalize the function over the domain. Neural network training is commonly posed as an optimization problem in the weight space. The non-linear least squares objective function in this case is defined by

$$\mathbb{E}(\vec{W}) = \sum_{k=1}^{I_t} e_k^2, \tag{1.9}$$

where I_t is the number of training patterns and

$$\varepsilon_k^2 = \Big(f(\vec{x}_k) - \hat{f}(\vec{x}_k)\Big)^2 \tag{1.10}$$

is the squared error associated with the training pattern k, f is the target or desired output, and $\hat{f}$ is the computed output corresponding to the input $\vec{x}_k$. The error vector is defined by

$$\vec{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{I_t})^\mathsf{T}. \tag{1.11}$$

In the rest of this paper I only discuss three layer neural networks consisting of an input layer, a hidden layer and an output layer. Furthermore, I consider fully connected networks in which a neuron will receive signals from each and every neuron in the immediately preceding layer.

1.2.3 *Merits of Neural Computing for this Dissertation*

Neural networks are inherently non-linear as described in Rumelhart and McClelland (1986) and Wasserman (1989). With neural networks using one or more hidden layers, the networks can partition the sample space automatically and build different functions in different portions of that space. Thus, the use of neural networks offers the following useful properties and capabilities:

1. Non-linearity: An artificial neuron can be linear or non-linear. Hence, they can extract any residual non-linear elements from the data after linear terms are removed.
2. Input-output mapping: The network can learn an input-output relations with a method called supervised leaning. This involves modification of the synaptic weights by applying a set of labeled training samples.
3. Adaptivity: Neural networks have a built-in capacity to adapt their synaptic weights to changes in the surrounding environment.
4. Evidential response: In context of pattern classification, a neural network can be designed to provide information not only about which particular pattern to be selected but also about the confidence in the decision made.
5. Contextual information: Every neuron in the network is potentially affected by the global activity of all other neurons in the network. Consequently, contextual information is dealt with naturally by a neural network.
6. Fault tolerance: A neural network implemented in a hardware form, has the potential to be inherently fault tolerant, or capable of robust computation, in the sense that its performance degrades gracefully under adverse operating conditions.
7. High-performance computing: The massively parallel nature of a neural network makes it potentially fast for computation of certain tasks. This same feature makes a neural network well suited for implementation using Very-large-scale-integrated technology (VLSI) technology.

Function approximation, or regression analysis, including time series prediction, fitness approximation and modeling is therefore only one particular task in the majority of various challenges like data processing or pattern recognition.

For empirical analysis I perform my network training with the FAUN neurosimulator. As described in Mettenheim and Breitner (2010) two reasons make FAUN suitable for HFT. Since my supervisor Michael H. Breitner started the FAUN project in 1996 there has been continuous development and improvement - see chapter 4 for further details. The neural network types and topologies supported are among the most powerful and worldwide accepted for real life problems.

1.3 RESEARCH DESIGN AND ORGANISATION OF MY DISSERTATION

This dissertation provides empirical evidence that neural networks can be used in order to achieve more accurate approximation as well as better decision making in financial markets. I perform several different empirical studies to investigate the approximation capability of neural networks in case of time series analysis and market price synthesis.

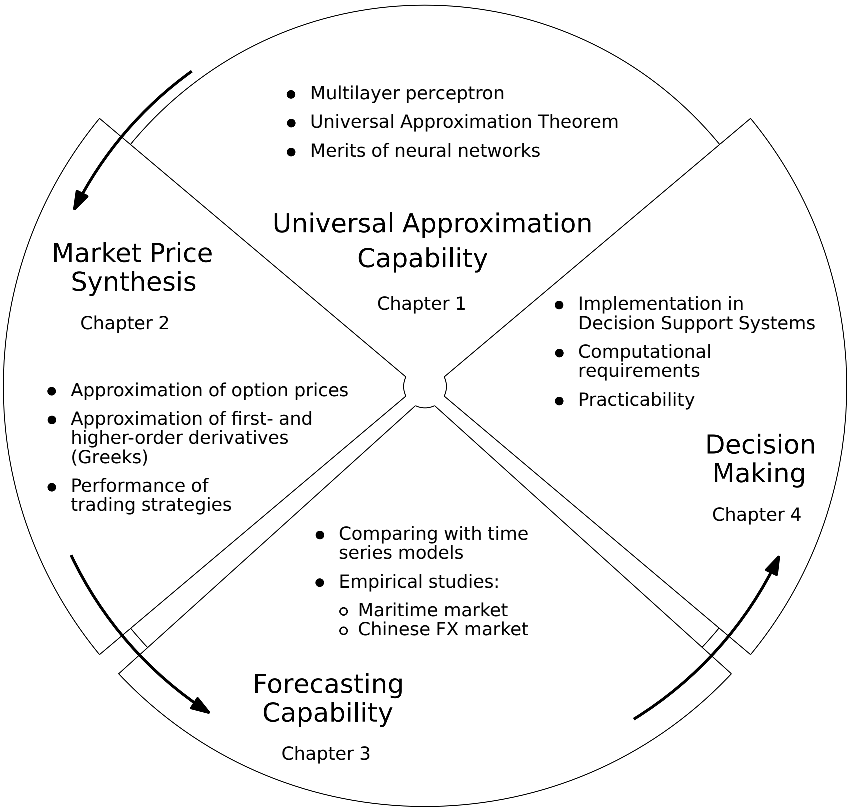
After theoretically explaining the approximation capability by neural networks, I approximate price functions of financial products - in this case for FX options - for real-time pricing using neural networks in chapter 2. The objective is to generate a functional relationship of the option price from existing market prices by a semi-heuristic approach. Market actors are able to conduct hedging strategies by deriving partial derivatives of first- and higher-orders. The generated network functions can also be used for real-time out-of-sample pricing and hedging.

In chapter 3, neural networks can also be used for forecasting financial market data, in which lagged time series data points are set as input variables. I consider both univariate and multivariate models. It is my objective to achieve accurate forecasting accuracy of existing data, but also to detect the unique market characteristics, e.g. the lead-lag relationship between the spot and derivatives market, volatility, and price behavior. Exemplary I have investigated the highly volatile maritime freight market and the Chinese FX market. Both disciplines, pricing approximation and time series analyzes, are based on a decision making process in practice.

In chapter 4 I present the use of neural networks in a model-driven decision support system. A computer-based decision making technique may be used for trading purposes in practice. Neural networks can meet computational and technical requirements that allows an algorithmic control. Figure 1.2 summarizes the organization of my dissertation.

In most studies, neural networks compete with particular benchmark models. In case of market price synthesis for options there is a broad range of analytical closed-form models like the famous Black-Scholes model. In the field of time series analysis neural networks can be seen as an alternative to regressive models with

Figure 1.2: Overview



constant and non-constant volatility. The comparison to the benchmark models is discussed in detail in chapter 2 and chapter 3.

Outside of my dissertation topic, I list a working paper about nomadic computing, which is quite a more information science orientated theme. The paper is not the result of my studies and treated a then still unknown and innovative topic. It describes the use of new mobile services with mobile devices and services from a business perspective. With advent of smart phones, the concept nomadic computing has been thoroughly worked up. However, and there are already new developments such as augmented reality for private customers. In this respect I did not even discuss this report, but the manifold implications from the implementation of intelligent systems.

1.4 EMPIRICAL STUDIES AT A GLANCE

In the second part of my dissertation I append all empirical studies on which this synopsis and critical review is based. The reader may consider a short summary of all papers in this section. I group the individual papers on the mentioned three application cluster market price synthesis, forecasting and decision making.

In order to approximate market prices I conduct an empirical run-time trading simulation with a tick data set of EUR/USD options on currency futures of four weeks. The high-frequency data set is very large and consists of more than 100,000 quotes. Due to the difficulty of option valuation, I provide an alternative model-free option pricing approach with neural networks, which can be embedded in a high-frequency trading process. In non-overlapping 15 minutes out-of-sample intervals theoretical option prices derived from the Black model compete against heuristic option prices through neural network models. In an earlier investigation "*Pricing and Forecasting of High-Frequency Options on Currency Futures with Fast Neural Networks*" (see Paper E) the preliminary focus lies on the pricing capability of network functions. I examine different topologies in order to achieve suitable results in comparison to the Black model. The paper "*Real-time Pricing and Hedging of Options on Currency Futures with Artificial Neural Networks*" (see Paper B) is an extension, where I optimize the network topologies in order to achieve better results than the benchmark model. In addition, I perform a bootstrap significance test and investigate the hedging performance of the network function. The latter issue is object of research in my last investigation "*Numerical Approximation of Option Pricing Functions and Its Partial Derivatives by Neural Networks*" (see Paper A). This paper addresses the partial derivations of generated network functions for hedging purposes.

Besides real-time pricing and hedging algorithms market actors are interested in dynamics and predictions of relevant market variables. This leads to examination of autoregressive time series processes and model specifications with lagged input variables. I perform my investigations in two interesting markets: The high-volatile shipping freight rates market and the revised Chinese FX market. In "*Freight Rates in the Tanker Shipping Market – Short-Term Forecasting of Spot Rates and Derivatives with Linear and Non-Linear Methods*" (see Paper F) and "*Spot and freight rate futures in the tanker shipping market: short-term forecasting with linear and non-linear methods*" (see Paper G) I investigate the forecasting and trading performance of linear and non-linear methods, in order to generate short-term forecasts of spot freight rates and corresponding freight derivatives respectively FFA in the dirty tanker shipping market. I attempt to uncover the benefits of using several time series models and the potential of neural networks. Maritime forecasting studies using neural networks are rare and only focus on spot rates, with the result that only longer forecasting horizons lead to encouraging results with neural networks. I build on this kind of investigation, but I extend my study on freight rates derivatives or FFA prices and a wider range of time series models. The field of attention in "*Short-Term Trading Performance of Spot Freight Rates and Derivatives in the Tanker Shipping Market: Do Neural Networks provide suitable results?*" (see Paper H) lies more in examination of the trading performance. In a simple empirical simulation I compare univariate and multivariate models results.

The Chinese FX market is a restricted currency market with different sub-currencies. Since 2011 China attempts to internationalize its currency by allowing more cross-border trade to be settled in RMB. In "*Forecasting Renminbi Quotes in the Revised Chinese FX Market – Can We get Implications for the Onshore/Offshore Spread-Behaviour?*" (see Paper C) we investigate the short-term forecasting performance of spot CNY with GARCH-type and neural network models in order to uncover the benefits of relationships between onshore and offshore RMB. This is achieved by simulating both RMB time series in a multivariate way. Our conclusion is, that our proposed models lead to a better understanding of the still young volatility behaviour of the two different RMB series.

Both market price synthesis and forecasting disciplines induce relevant trading decisions in financial markets. Hence, market actors need appropriate decision making techniques. In "*Steps towards a High-frequency Financial Decision Support System to Pricing Options on Currency Futures with Neural Networks*" (see Paper D) I present steps towards a model-driven DSS to pricing options on currency futures, which can be embedded in a high-frequency trading process. I show that the use of neural networks is not only suitable in generating accurate trading signals, but also in generating automated fast run-time trading signals for the decision taker.

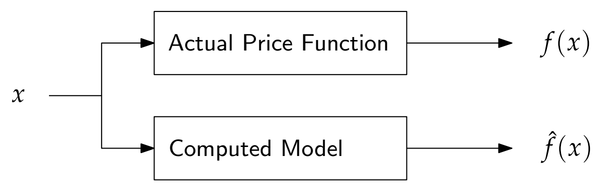
The last paper "*Geschäftsprozessorientierte Analyse und Bewertung der Potentiale des Nomadic Computing*" (see Paper J) is not explicitly part of my dissertation topic, but refers to a more business informatics field. Nomadic computing is a new paradigm of computer usability, in which the users from anywhere and at any time get access to data, information and services. I design a business framework in order toevaluate this technology. Beyond this paper I introduce the discussion about using artificial intelligence in social life and networks and for handling big data.

2 MARKET PRICE SYNTHESIS

2.1 APPROXIMATION OF PRICE FUNCTIONS AND THEIR DERIVATIVES

Learning an input-output relation from observable market prices can be considered as the problem of approximating an unknown function $f(x)$ from a set of data points. The general situation is as in figure 2.1, where the model $\hat{f}(x)$ has to be constructed based on finitely many observations on the target function $f(\cdot)$. For example, traders are interested in the price of financial option products, at now. There is a wide range of pricing models for this product: in some ways closed-form analytical models, for more complicated products numerical solutions. One further believes that the price of the option depends upon some parameters. Of course, no one knows a precise formula to compute this price as a closed-form function of the parameters, but only has available data on the many options traded on the market.

Figure 2.1: Market price synthesis scheme



There are two kinds of errors involved in using $\hat{f}(x)$ as a predictor for $f(x)$. The intrinsic error arises from the fact that I am computing a model rather than the actual function. The second, often called noise, comes from the fact that the observations on which the model is based contain errors. While the subject of statistics deals with the problem of making a model reliable by controlling the noise, the subject of approximation theory deals with the intrinsic error.

Neural networks are commonly used for function approximation, and they offer an alternative way of developing option pricing and hedging models. Their particular strength lies in their ability to approximate highly non-linear and multivariate relationships without the restrictive assumptions implicit in parametric approaches. This property of NNs makes them attractive for problems such as pricing and hedging options.

To be more specific, option pricing is based on theoretical models developed by Black and Scholes (1973), Merton (1973) and Cox et al. (1979) with several extensions. In each case, the derivation of the pricing formula intimately depends on the particular parametric form of the underlying asset's price dynamics S_t. A misspecification of the stochastic process for S_t will lead to systematic pricing and hedging errors for derivatives. Therefore, the success or failure of the traditional approach to pricing and hedging options is closely tied to the ability to capture the dynamics of the underlying asset's price process. Despite usefulness of closed-form type models, Black (1975), Rubinstein (1985) and Bakshi et al. (2000) emphasized that some models primarily address perceived weaknesses.

Unfortunately, theoretical pricing models are based on several unrealistic assumptions. First of all, markets are efficient, i.e., nobody can consistently predict the direction of the market or an individual underlying. Secondly, underlying prices follow a memoryless continuous-time or discrete-time stochastic process. In addition, the future volatility σ of the underlying price can be estimated accurately and is a priori known to seller and buyer of an option. Fourth, most of the option pricing models assume normal or log-normal distributions of asset returns. However, finding such a distribution in volatile environments means going beyond simple assumptions of normality or log normality used in conventional models. Hence, one must get its hands dirty in numerical approximation, and can no longer plug numbers into quick formulae based on normal distributions.

Table 2.1 summarizes the main differences and links between parametric models and NNs.

Table 2.1: Model typology

Parametric model	Neural networks
• Restrictive assumptions leading to systematic bias • Multivariate and non-linear • Fails to adjust to changing market behaviour • Easy to apply and no historical data is required	• Recognizes patterns and relationships without restrictive assumptions • Effectively approximates non-linear functions • They are adaptive and respond to structural changes in the data-generating processes and robust to specification errors that plague parametric models • Requires a large amount of data and is sometimes unable to converge rapidly

Network-based pricing methods for pricing and hedging derivatives attempt to overcome the mentioned restrictions in theoretical models. Rather than starting from a price process of the underlying asset and subsequently deriving the corresponding option value, the option market's pricing mechanism is estimated by means of observed prices via a neural network. When properly trained, the network synthesizes the option pricing formula, which may be used in the same way that formulas obtained from the parametric pricing method are used.

Another way to interpret an estimated model is to examine a few of the partial derivatives or the effects of certain input variables on the dependent variable. With these partial derivatives, one can assess, qualitatively and quantitatively, the relative strength of how input variables affect the dependent variable. There are two approaches: Analytical and finite-difference methods. Fortunately, computing such derivatives is a relatively easy task.

Of course, the network-based pricing method is highly data-intensive, requiring large quantities of historical prices to obtain a sufficiently well-trained network. Therefore, such an approach would be inappropriate for thinly traded derivatives, or newly created derivatives. However, I show in this chapter how the neural network performs when applied to high-frequency option data sets.

2.2 MODELLING FX OPTIONS BY NEURAL COMPUTATION

2.2.1 *Literature Review*

Previous studies about pricing options by neural computation show no ambiguous picture, if neural networks can generally outperform traditional closed-form models with satisfied robustness. Of course, many authors achieved better results by using neural networks - mostly for a particular time and asset classes. Table 2.2 shows an extract of different studies of pricing and hedging options by neural computation.

Hutchinson et al. (1994) compared three neural networks with the Black-Scholes (BS) model in pricing American-style call options on Standard Poor's (S&P)500 futures, and found that all three networks were superior to BS. Malliaris and Salchenberger (1993) compared the performance of the Black-Scholes model and a network-based model in pricing American-style S&P100 call options. They found that BS was preferable for in-the-money (ITM) options, whereas the network performed better for out-of-the-money (OTM) options. Lajbcygier et al. (1997); Lajbcygier and Connor (1997) compared three networks with three closed-form models - BS, Barone-Adesi and Whaley (BAW) and modified Black - in pricing American-style call options on Australian Share Price Index futures (SPI). They concluded that the learning systems were inferior to the theory-based models; however, for observations that were at-the-money (ATM) for short-maturity options, the networks were superior. Garcia and Gençay (2000) compared the performance of an neural network in pricing European-style call options on the S&P500 index with that of Black-Scholes and concluded that the neural network was superior.

In the following, Andreou et al. (2002), Amilon (2003), Bennell and Sutcliffe (2004) and Andreou et al. (2006) got similar encouraging results regarding European-style options. Many of these studies assume that their option pricing network formula

Table 2.2: Studies using NNs to price and to hedge financial options

Pricing options	S&P 500	Andreou et al. (2002, 2006, 2008, 2010), Garcia and Gençay (2000), Gradojevic et al. (2009)
	S&P 100	Malliaris and Salchenberger (1993)
	FTSE 100	Bennell and Sutcliffe (2004)
	DAX	Anders et al. (1998), Hanke (1999)
	OMX	Amilon (2003)
	S&P 500 Futures	Hutchinson et al. (1994), Carverhill and Cheuk (2003)
	SPI Futures	Boek et al. (1995), Lajbcygier et al. (1997); Lajbcygier and Connor (1997); Lajbcygier (2004)
	BASF	Breitner (2000)
	FX	Chen and Sutcliffe (2012)
	Simulated	Hutchinson et al. (1994), Hanke (1997), Kohler et al. (2006)
Hedging options	S&P 500	Andreou et al. (2008, 2010), Garcia and Gençay (2000)
	S&P 500 Futures	Hutchinson et al. (1994); Carverhill and Cheuk (2003)
	OMX	Amilon (2003)
	SPI Futures	Lajbcygier et al. (1997); Lajbcygier and Connor (1997); Lajbcygier (2004)
	Simulated	Hutchinson et al. (1994), Hanke (1997), Kohler et al. (2006)

is homogeneous of degree one in the underlying asset price S_t and in the strike price X which enables them to use a smaller number of inputs in learning the nonparametric pricing function. This parsimony is an advantage since the rate of convergence of nonparametric estimators slows down considerably as the number of input increases.

Due to the data-driven character of neural networks, some authors tested the approximation capability of neural networks with simulated data. This method ensures that learning networks get the full data space for training. Of course, there is no evaluation with market data possible. Hutchinson et al. (1994) did several Monte Carlo simulations in order to test the robustness of their proposed models. Hanke (1997) used simulated data to investigate the performance of neural networks in pricing Asian-style call options.

Further model extensions consider an adjustment of the network topology, e.g. Boek et al. (1995) and Lajbcygier et al. (1997) proposed hybrid neural networks, which combine theoretical option models with neural networks. These nested models often exceed the performance of other models. Gradojevic et al. (2009) performed a kind of regime-switching or modular network topology like, where the pricing function is decomposed into separate non-linearities called modules. The modules are trained independently on the data for the ITM and OTM options and during run-time pricing.

However, the heart in the option pricing theory lies in the replication of an option with an asset portfolio. Thus, the determination of price sensitivities of an option is crucial. Hedge ratios can be derived analytically from the chosen parametric pricing model. Since NNs are differentiable functions of the input variables, option sensitivities, namely the Greeks, such as the hedge ratio can also be derived analytical from the neural network pricing approximation. The proposed studies in table 2.2 conducted hedging strategies to evaluate partial derivatives derived by neural computation.

Alternatively, neural networks can be trained directly on the desired hedge ratios as described in Bengio (1997). Carverhill and Cheuk (2003) applied this technique to option prices. They found that the best delta hedging performance was produced by the binomial model, followed by the new neural network, while hedge ratios derived from the pricing network-based model were worst.

2.2.2 *Methodology and Implementation*

Research formulation

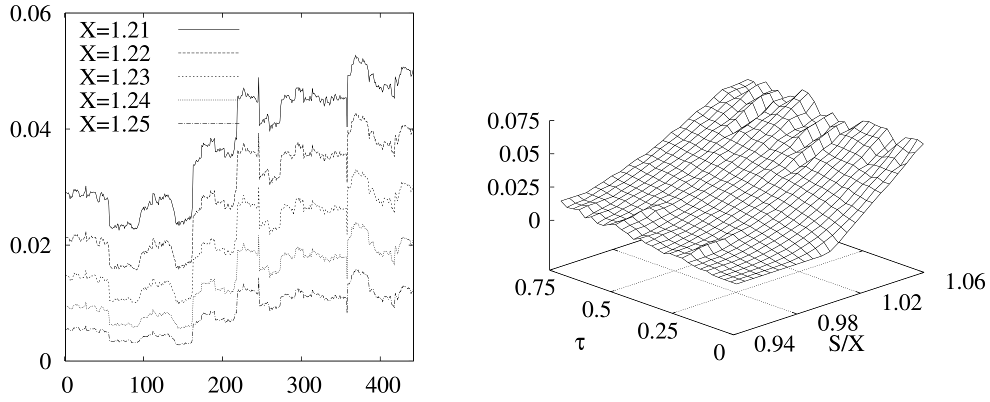
As before mentioned, subsequent studies mostly investigated daily equity index options data for option pricing approximations. Despite the high liquidity of FX options markets, there is no noticeable investigation about pricing FX options with neural networks in a HFT-context.

Hence, I build on prior investigations, but I extend my studies paper B and paper E with a run-time trading process in order to uncover special characteristics of high-frequency data. In particular, I pose the following challenge: If option prices were truly determined by the theoretical model exactly, can the closed-form formula be estimated by learning networks with a sufficient degree of accuracy to be of practical use? Furthermore, can both models be implemented in an automatic HFT trading process, in which a signal must be precise enough to trigger trades in a fraction of a second?

Data object

I sample intra-day prices of an EUR/USD option on currency futures with five different strike prices. These are derivative contracts that grant the purchaser the right, but not the obligation, to trade a EUR/USD futures contract, which is a contract to exchange EUR and USD at an agreed-upon exchange rate at a certain point in the future. A high-frequency data samples FX futures data of four weeks available from 13 August 2012 to 17 September 2012 (expiry date) by the Chicago Mercantile Exchange (CME). The options data is available from 13 August 2012 to 7 September 2012, due to the prior expiry of options to final settlement or expiration of the underlying FX futures contract. The data contains trade or quote prices, bid and ask prices and volumes. A UNIX timestamp in milliseconds records the date and the time at which the quote originates. Due to the high-frequency character of tick data, I match the nearest futures quote or available trade price with the relevant option price. For high-frequency data cleaning it is necessary to implement automatic procedures based on different criteria in order to decide on the possible elimination of each observation. In summary, I obtain a full data set of 118,291 quotes and prices after data cleaning for training and out-of-sample evaluation (figure 2.2a).

Figure 2.2: High-frequency CME option data and simulated American call option prices



(a) EUR/USD FX options on currency futures

(b) Surface of simulated call option prices

In a further simulation experiment (paper A) I investigate the numerical approximation of option pricing functions and their derivatives by neural networks. I am also interested in the question of whether the data availability is crucial for a better approximation. For this purpose I generate simulated more than 20,000 high-frequency option prices to get a broader range of data (figure 2.2b).

Implementation

To assess the potential value of network pricing formulas in HFT, I implement two different investigations. First, paper B and paper E perform a rolling 15 minutes out-of-sample interval for each trading day to assess the models pricing ability. The derived approximation function is then used to perform a delta-hedging examination. All results are benchmarked using a theoretical closed-form model for pricing options on futures. Second, in order to carry out the approximation capability of the network function and its partial derivatives paper A trains on the full data set without any rolling-window technique.

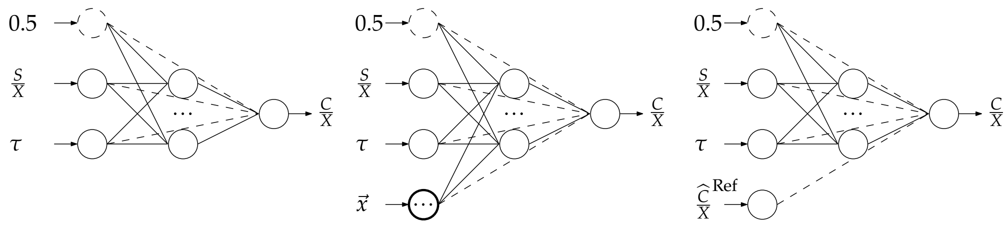
Specification

The network specifications declines mainly to the parsimonious parameterizations as proposed in Hutchinson et al. (1994), i.e., only two observable variables are necessary. This network specification in figure 2.3a is the standard topology in all my studies. From this several extensions are possible. I test various topologies like in figure 2.3b, where I add further variables $\vec{x} = (t, X, \sigma_S, r)^{\mathsf{T}}$. I also specify so-called hybrid models. Either the network trains directly on the difference between the market option price and the benchmark model price or the benchmark model price is directly linked to the output neuron in figure 2.3c.

Evaluation

It still remains to be examined how far the different network specifications lead to good out-of-sample pricing performance. To compare the observed market prices C_t with those obtained by traditional models statistical performance measures, least square errors are reported. As option pricing models are frequently used to calculate hedge parameters, it is necessary to check whether the parameters obtained by the neural networks are reliable in so far as they satisfy theoretical

Figure 2.3: Various network topologies



(a) Parsimonious model **(b)** Extended model **(c)** Hybrid model

theoretical patterns: The network-based models have to be able to hedge an option position.

Following Hutchinson et al. (1994), I investigate the tracking error of replicating portfolios designed to delta-hedge an option in paper B. Another way of assessing model performance is to trade in mispriced options in order to yield a higher final value, which is shown by Amilon (2003). The tracking error at the termination of the hedge position can be used as a measure of accuracy. Since all prices and hedge ratios are calculated theoretically, the model with the lowest absolute tracking error has best captured the dynamics of the underlying asset. In paper A I derive further price sensitivities and compare the surface of price sensitivities with the market price substitution derived by the BAW pricing method.

2.3 EMPIRICAL FINDINGS

I examine both the pricing accuracy and delta-hedging performance. The results are encouraging in the sense that they simultaneously provide accurate market prices for different strike prices. Although nonparametric pricing formulas are slightly better, the results show that the pricing accuracy for nonparametric learning networks depends on the availability of data, which reflects the state space. This reflects in particular the approximation of partial derivatives. I draw the following conclusions:

- Model option prices derived from networks can synthesize option market prices in a similar manner, but in a simultaneous way and with a more parsimonious input specification. There is e.g. no need of volatility or interest estimation.
- This argumentation is also valid in case of HFT data (empirical and simulated data), i.e., learning and real-time pricing in very short time periods.
- If market liquidity exists, which is equivalent to full data availability in a particular state space, learning networks are capable to approximate first- and

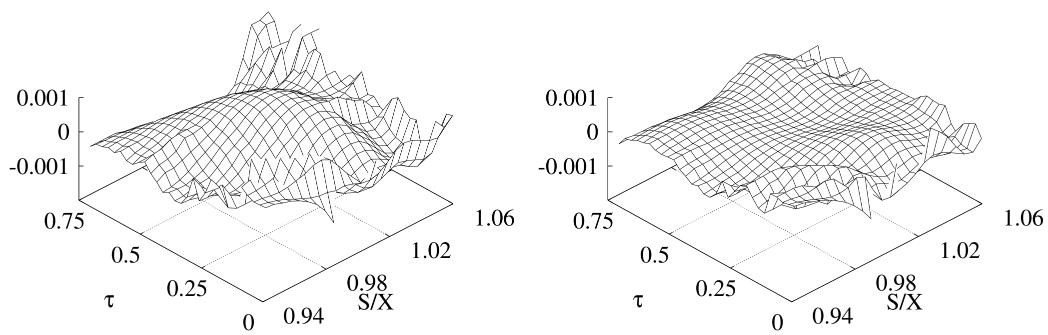
higher-order partial derivatives with a sufficient accuracy. But the approximation accuracy decreases with higher-order partial derivatives.

- Incorporation of further input variables, e.g. σ_F or r, do not necessarily improve the network results. Conversely, the pricing and hedging accuracy of all mentioned benchmark models highly depend on the unobservable volatility estimate. Thus, ones can control benchmark results by accurately estimation of this parameter. Several studies assume a constant volatility over time, which is quite imprecise.

- However, I can not confirm the hypothesis that once a predominant network approximation is found for pricing purposes, the same could be applied for hedging. I have to notice that it is an exhausting balancing act for learning systems to apply the delivered pricing approximation function on unknown hedge parameters.

In summary, the results are encouraging in the sense that I get a good fit of the data though training big HFT time series simultaneously. The approximation results are close related to the selected number of hidden neurons. As figure 2.4 illustrates the pricing error declines with additional neurons. Not very surprisingly, the computing time increases - I come back again to this fact in chapter 4.

Figure 2.4: Network pricing errors $\frac{C}{X} - \frac{\widehat{C}}{X} \ldots$



(a) . . . with 2 hidden neurons

(b) . . . with 5 hidden neurons

From this point of investigation, further research steps are thinkable and I recommend to augment network topologies to achieve more robust results. Nevertheless, I think that neural networks could be a useful HFT support system beside closed-form models for particular market situations. The benefits of the FAUN technology as a kind of core engine allow both option sellers and buyers to approximate call option prices across different strike prices simultaneously and with parsimonious input specification.

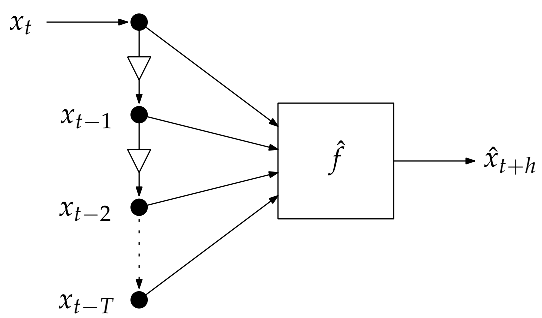
3

FORECASTING FINANCIAL TIME SERIES

3.1 TIME SERIES MODELING BY NEURAL COMPUTING

Due to the increasing volatility in financial markets, forecasting market prices has become more relevant for management decisions. Obtaining an effective and accurate prediction of asset prices supports decision makers in reaching a variety of decisions, such as storage decisions, buy and hold decisions or hedging decisions. Theoretically, the efficient market hypothesis implies that in an efficient market, it is impossible to obtain better forecasts using forecasting methods because the observable price already reflects all available information and price fluctuations in the future occur randomly. In reality, however, systematic patterns might be found in financial sequences. Knowing and discovering these structures will facilitate the process of price-forecasting. But one has to know which approximating models to use, in combination with past data, to predict future events.

Figure 3.1: *h*-step forecasting model scheme



Consider a univariate time series x_t, which, for simplicity, is observed at equally spaced time intervals. I denote the observations by $\{x_t | t = 1, \ldots, T\}$, where T is the sample size. If there is a functional relation between the successive observations, one can try to formulate a linear or non-linear prediction model of the time series (3.1).

According to Tsay (2002), a purely stochastic time series x_t is said to be linear if it can be written as

$$x_t = \alpha + \sum_{i=0}^{\infty} \beta_i a_{t-i}, \tag{3.1}$$

where α is a constant, β_i are real numbers with $\beta_0 = 1$, and $\{a_t\}$ is a sequence of independent and identically distributed (iid) random variables with a well-defined distribution function. Assuming that the distribution of a_t is continuous and $\mathbb{E}(a_t) = 0$ and $\mathbb{V}(a_t) = \sigma_a^2$. A commonly used linear model for forecasting is the autoregressive model. Any stochastic process that does not satisfy the condition of equation 3.1 is said to be non-linear.

Mathematically, a purely stochastic time series model for x_t is a function of an iid sequence consisting of the current and past shocks - that is

$$x_t = f(a_t, a_{t-1}, \ldots). \tag{3.2}$$

The linear model in equation 3.1 says that $f(\cdot)$ is a linear function of its arguments. Any non-linearity in $f(\cdot)$ results in a non-linear model. The general non-linear model in equation 3.2 is not directly applicable because it contains too many parameters.

Moreover, the model of x_t can be written in terms of its conditional moments. Let $\mathcal{F}_{t-1}$ be the σ-field generated by available information at time $t-1$. Typically, $\mathcal{F}_{t-1}$ denotes the collection of linear combinations of elements in $\{x_{t-1}, x_{t-2}, \ldots\}$ and $\{a_{t-1}, a_{t-2}, \ldots\}$. The conditional mean and variance of x_t given $\mathcal{F}_{t-1}$ are

$$\mu_t = \mathbb{E}\left[x_t | \mathcal{F}_{t-1} \equiv g(\mathcal{F}_{t-1})\right], \quad \sigma_t^2 = \mathbb{V}\left[x_t | \mathcal{F}_{t-1} \equiv h(\mathcal{F}_{t-1})\right], \tag{3.3}$$

where $g(\cdot)$ and $h(\cdot)$ are well-defined functions with $h(\cdot) > 0$. Thus, I restrict the model to

$$x_t = g(\mathcal{F}_{t-1}) + \sqrt{h(\mathcal{F}_{t-1})}\varepsilon_t,$$

where $\varepsilon = a_t/\sigma_t$ is a standardized shock. For the linear series x_t in equation 3.1, $g(\cdot)$ is a linear function of elements of $\mathcal{F}_{t-1}$ and $h(\cdot) = \sigma_a^2$. the development of non-linear models involves making extensions of the two equations in equation 3.3. If $g(\cdot)$ is non-linear, x_t is said to be non-linear in man. If $h(\cdot)$ is time-variant, then x_t is non-linear in variance.

Bollerslev (1986) provide a survey of the existence of non-linearities in the financial data, and developed a model to predict financial time series called Generalized Autoregresssive Conditional Heterocedasticity (GARCH) that combines all the features observed in these series. These conditional heteroscedastic models are non-linear in variance, because their variances σ_t^2 evolve over time. They are extensions of the conditional variance equation 3.3.

To locate the neural network model among different typologies of models, table 3.1 differentiates between parametric and semi-parametric models, and models that do not have closed-form solutions.

The most commonly used approximation method is the polynomial expansion, which has the flexibility to represent very general non-linear relationships. Approximation of more complicated functions by polynomials is a basic building block for a great many numerical techniques. With a polynomial or neural network model,

Table 3.1: Model typologies; McNelis (2005)

Closed-form solution	Parametric	Semi-parametric
Yes	Linear	Polynomial
No	GARCH	Neural network

the functional forms are given, but the degree of the polynomial or the number of neurons are not. Thus, the parameters are neither limited in number, nor do they have a straightforward interpretation, as the parameters do in linear or GARCH models. But the price one has to pay for an increasing degree of accuracy is an increasing number of parameters to estimate, and thus a decreasing number of degrees of freedom. For this reason, I refer to these models as semi-parametric.

Substantial benefit can be had from orthogonal polynomials. Orthogonal polynomials can be used to minimize the error of approximation, and to minimize the sensitivity of calculations. Unlike the typical polynomial based on raising the variable x to powers of higher order, these classes of polynomials are based on sine, cosine, or alternative exponential transformations of the variable x. They have proven to be more efficient approximators than the power polynomial. The network is an alternative to the parametric linear, GARCH models, and semi-parametric polynomial approaches for approximating a non-linear system.

It has often been found that simple linear time series models usually leave certain aspects of economic and financial data unexplained. Since non-linear models are more general than the linear ones, one would expect that neural networks should lead to better forecasts. However, financial time series are seldom easy to handle. The goal is to find an approach or method that forecasts well data generated by often unknown and highly non-linear processes, with as few parameters as possible, and which is easier to estimate than parametric non-linear models.

Both the GARCH and neural network are examples of models that do not have closed-form solutions for the coefficient vector of the respective model. What is clear from table 3.1, moreover, is that one has a clear-cut choice between linear and neural network models. The linear model may be a very imprecise approximation to the volatile financial markets, but it gives very easy, quick, exact solutions. The neural network may be a more precise approximation, capturing non-linear behavior, but it does not have exact easy-to-obtain solutions. Without a closed-form solution, one has to use approximate techniques.

The rationale for the use of the neural network is forecasting or predicting a given target or output variable from information on a set of observed input variables (Hill et al. (1994)). To test the application of neural networks for the prediction of time series, I show empirical examples of two different financial markets in the following: First, the freight market is a representative of an extremely volatile market. Information about the future quotation of freight rates, the relationships between spot and forward contracts and price dynamics are of interest here. Second, the Chinese FX market is, however - according to a revision - a very young market, whose behaviors have not yet been thoroughly investigated. I am particularly interested in the relationship between the sub-currencies - the onshore and offshore Renminbi.

3.2 FORECASTING SHIPPING FREIGHT RATES BY NEURAL COMPUTATION

3.2.1 *The Shipping Freight Rates Market*

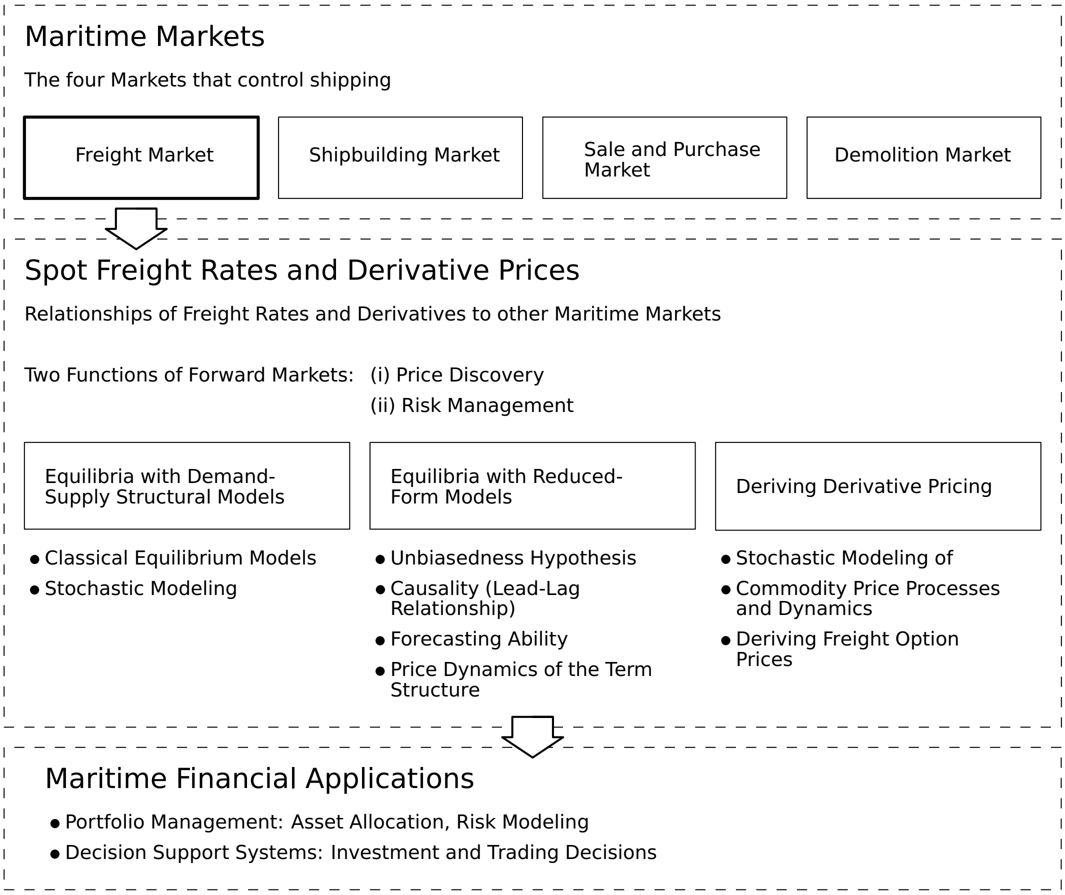
In an industry that is characterized by highly volatile prices, seasonality, strong business cycles, cyclicality and capital intensiveness, risk management is extremely important. Ship-owners and charterers face enormous risks, which emanate from fluctuations in freight rates, bunker prices, interest rates, foreign exchange rates and vessel values. These risks substantially affect the interplay between revenue and costs. Modern risk management techniques, involve the use of financial derivatives products, some of which have been developed exclusively for protecting or hedging against the adverse price fluctuations of the before mentioned sources of risk in shipping.

Freight derivatives have the potential to offset freight rate risk of the dry bulk and wet bulk sectors of the shipping industry and its support industries. The primary benefits futures markets provide to economic agents are price discovery and risk management through hedging. Price discovery is the process of revealing information about future spot prices through the futures markets. Risk management refers to hedgers using futures contracts to control their spot price risk. The dual roles of price discovery and risk transfer provide benefits that cannot be offered in the spot market alone and are often presented as the justification for futures trading.

Broadly speaking, modeling the freight rates market can be classified into three thematic approaches: Equilibria with demand-supply structural models, equilibria with reduced-form models, and deriving shipping derivatives prices - see figure 3.2.

First, structural models provide integrated econometric models of freight rates and a complete model of freight rate relations by using the demand-supply mechanism. The key feature of this work is not in the econometrics; rather it is the seminal development of a coherent explanation of ship price behaviour, which is grounded in the application of the two basic hypotheses of rational expectations of freight prices and market efficiency. These classical equilibrium models capture well some features of shipping market structure and provide many economic implications. Beenstock (1985); Beenstock and Vergottis (1989b,a), Tvedt (2003b), Adland and Strandenes (2007) and Tezuka et al. (2012) developed shipping equilibrium models. However, it is difficult to apply these models directly in practical situations, because there are many parameters needed for estimation. Thus, this interesting methods are not part of my studies.

Figure 3.2: Model classification of the shipping freight rates market



Second, the recent focus of exploring the relationship between spot and forward rates has been on re-examining the statistical properties of shipping market data by using reduced-form models or time series analysis. Reduced-form models are suitable and easily to implement for detecting main characteristics of the relationship between spot and forward commodity prices.

Grammenos (2002), Stopford (2008) and Alizadeh and Nomikos (2009) documented well that freight rates at any point in time reflect the balance between supply and demand for shipping services, which in turn depends on factors such as world economic activity, the stock of fleet, political events, and the international commodity trade. In other words, freight rates are formed through the interaction between shipping supply and demand schedules.

Across time, spot and forward prices are mutually linked by the cost-of-carry relationship, which plays a central role in pricing of derivatives. Thus, the price of a forward contract for a storable commodity, must be equal to the spot price of the commodity today plus the financial and other costs, e.g. storage and insurance, to carry it forward in time. If this is not the case and the forward price is overpriced (underpriced), arbitrageurs can simultaneously sell (buy) the forward contract, buy (sell) the underlying commodity and store it until the expiry of the contract. At expiry, reversing these positions will produce a risk-free profit. These movements by arbitrageurs ensure that correct prices always prevail in efficiently working markets, and they will be

$$F_t = S_t + \kappa_{T-t}, \tag{3.4}$$

where, F_t is the price of the forward contract at time t, S_t is the spot price of the underlying commodity and κ_{T-t} is the costs of carrying the commodity forward in time between period t and T. This feature of the underlying commodity of the derivatives contract violates the usual arbitrage arguments, that leads to the pricing of futures and forward contracts in storable commodities. In this case pricing of the futures or FFA contracts with the freight service as the underlying commodity is described though the following relationship

$$F_t = \mathbb{E}[S_T], \tag{3.5}$$

where $\mathbb{E}[S_T]$ denotes the expected value of S_T, with expectations formed at time period t. Forward prices are formed in terms of market expectations that will prevail at the maturity of the derivatives contract. Assuming rational expectations, the above equation becomes

$$F_t = S_t + \epsilon_t; \quad \epsilon_t \sim iid(0, \sigma^2). \tag{3.6}$$

Provided the relationship is verified with actual data, it can be argued that the freight forward market satisfies its price discovery function. This is cause, forward prices today help as discover spot prices in a future time period, specifically at the expiry of the derivatives contract.

However, due to their non-storable character, freight rates provide different patterns in contrast to other commodities. The hypotheses of rational expectations of freight prices and market efficiency is explored by testing particular characteristics of spot-forward relationships:

- The unbiasedness hypothesis may provide insight to whether the futures can be used to guide physical market decisions. In speculatively efficient markets for non-storable commodities, forward prices are unbiased estimators, i.e. there is no spread between spot and forward rates and all available information must be reflected in the price of a future. The thinness of the FFA market and the absence of a strong speculative interest mean that forward freight rates may exhibit neither of these properties.

- The lead-lag relationship between future prices and spot rates refers to how well the two markets are linked and how fast one of the markets reflects new information relative to the other. Assuming that new information is available to both markets at the same time, the markets should theoretically react simultaneously. Due to their non-storable character, futures prices may not contribute to the discovery of new information to the same extent as the markets for storable commodities.

Third, spot and forward prices are random; hence, need to be modeled. The objective is how these models can be adjusted to the specific properties of commodity prices. Spot freight rate models have been restricted to simple parametric models adopted from financial economics: The Geometric Brownian motion, the Ornstein-Uhlenbeck process, and the lognormal process of Brennan and Schwartz. These well-known models are convenient as they usually facilitate closed-form solutions for the term structure of freight rates and certain freight rate contingent claims.

3.2.2 *Literature Review*

A number of related studies have been published regarding to the term structure of spot and forward rates.

According to the unbiasedness hypothesis, Fortenbery and Zapata (1997) found that in the thinly traded market of cheddar cheese in the US, futures contracts price new information independently from the underlying spot market and consequently do not contribute to the discovery of new information regarding the future spot prices. In case of freight rates Veenstra (1999) supported the existence of a term structure in ocean spot and future freight rates. In the following, Kavussanos and Nomikos (1999); Kavussanos and Alizadeh (2002); Kavussanos et al. (2004) and Alizadeh et al. (2007) investigated the unbiased expectations property of the forward prices in the market. They found that futures prices one and two months before maturity are unbiased forecasts of the underlying spot prices. Futures prices three months before maturity are however found to be biased. Adland and Culliane (2005) presented a simple argument for rejecting the applicability of the expectations theory in bulk shipping freight markets. Kavussanos and Visvikis (2004) examined also the lead-lag relationship between OTC FFAs and spot returns. They found that FFAs have a leading role.

Freight forwards may have forecasting abilities regardless of whether the unbiased hypothesis holds. These price discovery properties may be investigated by comparing forward prices to forecasts generated by time series models. Building forecasting models for the FFA market is interesting for three reasons: First, forward rates are not tied to spot rates through a no-arbitrage condition, but are free to be determined by speculative activity. Second, there are asymmetric transactions costs between spot and FFA markets. These costs are believed to be higher in the spot freight market as they involve the physical asset, the vessel. Third, the forward freight market is relatively new and, like all forward markets, has developed primarily in response to the needs of hedgers. FFA prices can enhance the forecasting performance of spot prices.

Culliane (1992) and Culliane et al. (1999) reported success in forecasting spot freight rates by using univariate autoregression techniques. Alizadeh and Nomikos (2003) examined the directional forecast accuracy of FFAs and BIFFEX in four routes and concluded that FFAs do not seem to be very accurate in revealing the direction of future freight rates, and, in general, forecasting accuracy declines as maturity increases. Veenstra and Franses (1997), Kavussanos and Nomikos (2003) and Batchelor et al. (2007) compared the performance of multivariate models in generating short-term forecasts of spot freight rates and FFA prices. It seems that spot prices cannot help in enhancing the forecasting performance of FFA prices, which indicates that the forward rate does contain significantly more and different information than is embodied in the current spot rate. They found that forward rates do help to forecast spot rates, suggesting some degree of speculative efficiency. However, in predicting forward rates, the Vector Error Correction Model (VECM) is unhelpful, and Autoregressive Integrated Moving Average (ARIMA) or Vector Autoregression (VAR) models forecast better.

However, the use of linear time series models for freight rates is sometimes criticized, due to the fact that most financial time series show non-linear patterns - see Adland and Cullinane (2006) and Goulielmos and Psifia (2009). As a representative of non-linear methods, neural networks could be implemented for several financial applications. Li and Parsons (1997) investigated the potential of feedforward neural networks for short- to long-term prediction of monthly tanker spot freight rates. Their evidence shows that neural networks can significantly outperform time series models, especially for longer-term forecasting. In another study Lyridis et al. (2004) attempted to uncover the benefits of using neural networks in forecasting VLCC spot freight rates. Neural Networks demonstrated mean errors comparable to benchmark model for 1-month forecasts but significantly outperformed it in the 3-, 6-, 9- and 12-month cases. However, investigations of freight rates with neural networks is scarce.

Hence, while the development and subsequent growth in the freight derivatives market have enabled participants in the shipping industry to hedge their freight and cash flows, the process of assessing, modeling, and managing freight market volatility is still a difficult one. An abundance of studies have been carried out in an attempt to understand the time-varying characteristics of freight rate volatility, yet among them only a few have discussed what are the causes and impacts of the time-varying risk in shipping markets.

Kavussanos (1996) found that the pattern and magnitude of time-varying volatilities in the dry bulk freight markets are different across vessel sizes. In particular, freight rates for larger vessels tend to be more volatile than smaller ones. Chen and Wang (2004) and Jing et al. (2008) also examined the asymmetric characters of daily return volatility in different bulk shipping sectors and different market conditions by EGARCH models. The results show that the asymmetric characters are distinct for different vessel size segments and different market conditions. Glen and Martin (1998), Jia and Adland (2002) and Batchelor et al. (2005) performed similar investigations. Alizadeh and Nomikos (2011) investigated the relationship between the dynamics of the term structure and time-varying volatility of shipping freight rates. They found support for the argument that the volatility of freight rates is related to the shape of the term structure of the freight market. Furthermore, it is found that this relationship is asymmetric in the sense that when the freight market is in backwardation, volatility is higher compared to periods when the market is in contango. Xu et al. (2008, 2011) studied the relationship between the time-varying volatility of dry bulk freight rates and the change of the supply of fleet trading in dry bulk markets. Their results revealed that the change in fleet size positively affects freight rate volatility, while the spot rate volatility of capesize dry bulk exhibits a stronger reaction to the change in fleet size.

Little research work has been conducted on stochastic modeling freight rates and derivatives by using fundamental stochastic models. Tvedt (2003a), Koekebakker and Adland (2004) and Adland et al. (2007) performed investigations. The closed form of valuation formulae for options on shipping forward contracts is derived using the relationship between spot freight rates and forward prices. Tvedt (1998), Koekebakker et al. (2007) Wang et al. (2009) set up the theoretical framework for the valuation of the Asian-style options traded in the freight derivatives market. They suggest approximate dynamics in the settlement period for the FFA that leads to closed-form option pricing formulas for Asian call and put options written on the spot freight rate indices in the Black framework. But in fact, empirical research of freight options is very difficult due to the lack of data.

3.2.3 *Methodology and Implementation*

Research formulation

In paper A, paper G and paper H I perform different forecasting methods in order to examine the forecasting ability of freight rates. I find a lack of jointly spot and forward forecasting investigations with neural networks. Thus, I build on prior investigations, but extend my study on freight derivatives and a wider range of time series models. The main objective of this paper is to investigate neural networks' prediction ability for maritime business forecasting and provide a practical framework for actual forecasting and trading applications of neural networks.

Data object

I sample daily prices of the International Maritime Exchange (Imarex) TD3 and TD5 freight forward contracts. These contracts are written on daily spot rates for TD3 and TD5 published by the Baltic Exchange. The spot and FFA data is available from 5 April 2004 to 1 April 2011. For purpose of forecasting, each data set is divided into two subsets: The first subset runs from 5 April 2004 to 16 February 2010, the second subset from 17 February 2010 to 1 April 2011. The first subset is used to estimate the statistical models and identify the neural network structure while the second is used only for out-of-sample prediction comparison. This implies that I get a sample of 1466 daily observations for the estimation period and a sample of 282 daily observations for the forecasting period - a ratio of 5.25 to 1. Figure 3.3a shows the two spot freight rates.

Implementation

I investigate short-term forecasts of spot and FFA prices in the market in order to to make inferences about the efficiency and usefulness of FFA rates. The question arises: Are forward rates expectations of spot rates? A one-step ahead forecast of spot freight rates returns $\Delta\hat{S}_t$ and forward rates returns $\Delta\hat{F}_t$ is computed using lagged input variables in a univariate way as follows

$$\Delta\hat{S}_{t+1} = f(\Delta S_t, \Delta S_{t-1}, \ldots, \Delta S_{t-p})$$
$$\Delta\hat{F}_{t+1} = f(\Delta F_t, \Delta F_{t-1}, \ldots, \Delta F_{t-p})$$

and in a multivariate way

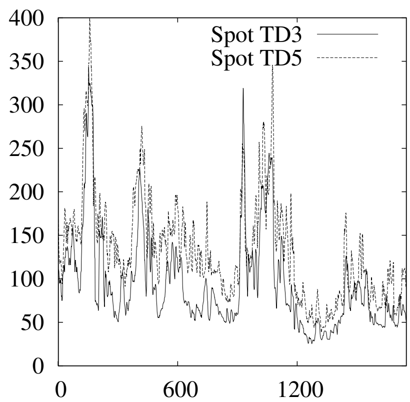
$$\Delta\hat{S}_{t+1} = f(\Delta S_t, \Delta S_{t-1}, \ldots, \Delta S_{t-p}, \Delta F_t, \Delta F_{t-1}, \ldots, \Delta F_{t-p})$$
$$\Delta\hat{F}_{t+1} = f(\Delta S_t, \Delta S_{t-1}, \ldots, \Delta S_{t-p}, \Delta F_t, \Delta F_{t-1}, \ldots, \Delta F_{t-p}),$$

where $f(\cdot)$ denotes the function determined by the network and ΔF_t and Δ_t are changes in log futures and spot prices, respectively. Thus the neural network is equivalent to the non-linear autoregressive model for time series forecasting problems.

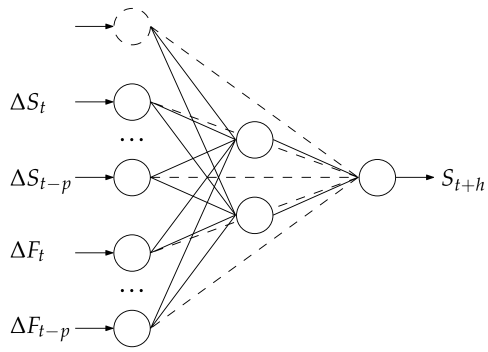
Model specification

I separate all models in univariate and multivariate model classes: The univariate models consist of an ARIMA and a NN model, where I include only the relevant single spot or FFA time series. For the multivariate models VAR, VECM and a multivariate neural network, I include both spot and all FFA rates of each route. All models, estimated over the initial estimation period, are used to generate one-step ahead, or $h = 1$, out-of-sample forecasts.

Figure 3.3: Examined freight rates and neural network specification



(a) TD3, TD5 spot rates



(b) Multivariate network specification for spot rate forecasting

The general approach used in the neural networks is to use historical values of the time series to train the network and test it with new values. Sliding the training window one step at a time I can extract $N - p$ training examples from a time series with N data points. After several training steps I can measure how well the network has learned to forecast the future. This technique corresponds to the autoregression models popular among statisticians.

Evalution

Typically, modeling techniques are optimized using a mathematical criterion, but ultimately the results are analyzed on a financial criterion upon which is not optimized. In other words, the forecast error may have been minimized during model estimation, but the evaluation of the true merit should be based on the performance of a trading simulation. Hence, I evaluate my forecasting results in a simple trading simulation, which is a better indicator for trading purposes than forecasting performance measures.

3.2.4 *Empirical Findings*

Spot and forward freight rates time series exhibit certain characteristics. Assuming that new information is available to both markets at the same time, the markets should theoretically react simultaneously. Due to their non-storable character, futures prices may not contribute to the discovery of new information to the same extent as the markets for storable commodities. There is evidence that forward rates tend to discover new information more rapidly than spot prices:

- The multivariate models confirmed this by generally providing more accurate forecasts than their univariate cousins. I observe this advantage especially for spot freight rates. These results imply that the futures prices contain valuable information about future spot rates.

- Vice versa forecasting FFA rates are much harder to forecast than the spot rates.

- Furthermore, the VECM, which has an equilibrium correction feature, perform better than VAR models for forecasts of spot rates, but not for forecasts of FFA rates.

- Changes in spot rates are explained by autocorrelation and by changes in the forward rates; but: Changes in forward rates are not explained by past changes in spot rates.

- There is, however, a highly significant autocorrelation in forward rates that is difficult to conciliate with efficient markets.

The rational expectations hypothesis seems to depend on the route in question and time to maturity. For short-term horizons (two month prior to maturity) mostly indicate that freight future prices are unbiased. In particular, I highlighted the forecasting capability of neural networks:

- The neural network results are comparable to those of the other models. It is interesting that the univariate NN achieve relatively good results, but the multivariate NN is not able to reinforce this advantage significantly.
- It seems, that the neural network as a non-linear approximator is already able to extract sufficient information out of the univariate time series. The additional information contained in other time series is therefore not needed.
- With respect to the important measures of net gain and risk-adjusted return as measured by the Sharpe ratio the univariate NN and multivariate VECM shows relatively good and stable results. I conclude, that both VECM and univariate NN may generate more robust trading results for this time series and perform better than the other forecasting models.

For shipowners and charterers, the findings of my study are encouraging, in the sense that they suggest that spot freight rates are forecastable, and the rates offered by Forward Freight Agreements to some extent help anticipate spot freight rates. For analysts of commodity markets the message is more cautionary, an illustration of the dangers of forecasting with an equilibrium correction model when the underlying market is evolving, and the parameter estimates conflict with sensible theoretical priors.

3.3 FORECASTING THE CHINESE FX MARKET BY NEURAL COMPUTATION

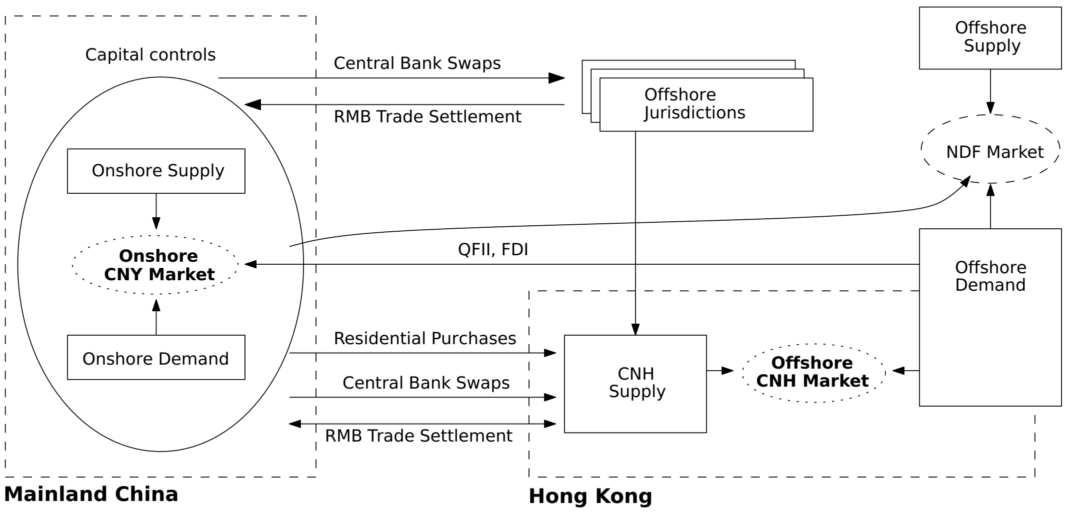
3.3.1 *The Chinese FX Market*

I will rather focus on one of the most unique features of the Chinese foreign exchange markets: the dual characteristic of the market (shown in figure 3.4). The uniqueness comes from the two separated markets for the RMB, namely the and market. The CNY stands for the inconvertibility of the Chinese currency under the capital account. The CNH market in Hong Kong is effectively a separate currency altogether, neither a perfect proxy for the onshore CNY, nor for the NDF (forward) curve market. The latter's otherwise known as the offshore dollar settled non-deliverable forward market, which is the traditional domain of offshore participants.

Recent reforms introduced by the Chinese authorities have sought to increase the use of the RMB in international trade and investment. In contrast to a few years ago, it is now possible for any trade transaction with China to be contracted in RMB. While the development of the offshore market for RMB has been a key part of the reform strategy, capital controls restrict the flow of funds between the onshore and offshore markets, thereby preventing full convertibility.

The Bank of China, however, provides an important link between the two markets, since it is permitted to undertake cross-border transactions subject to specified controls. Permitted cross-border flows between the onshore and offshore markets

Figure 3.4: RMB FX market: three different currencies; HSBC



have thus far been largely related to the RMB trade settlement scheme, although this may change as restrictions on cross-border flows are eased. An accumulation of RMB offshore has occurred as RMB-denominated imports into China have generally outweighed RMB-denominated exports from China under the scheme. This has likely largely reflected the incentive for foreigners to acquire and hold RMB when the RMB exchange rate has been expected to appreciate. RMB can also flow to and from the Mainland via some investment schemes, although it is unclear how extensively these have been used to date, given the existence, in many cases, of quotas and approval lags.

There has been some tendency for the offshore CNH exchange rate to converge to the onshore CNY exchange rate in recent years. Up until late last year, there was typically a small premium in the CNH rate - that is, one US dollar bought less yuan offshore than onshore - reflecting the expectation of some near-term appreciation of the CNY rate. The tendency for convergence over the past few years has been made possible by the ability to use trade flows, particularly between affiliated companies in the Mainland and Hong Kong, to arbitrage between the two exchange rates. However, increased concerns about the euro area debt crisis and the outlook for the US economy late last year resulted in a temporary reversal of this premium as offshore investors undertook a broad-based liquidation of emerging market investments, including those in the offshore RMB market. As a result, the offshore CNH exchange rate traded at a sizeable discount to the onshore rate for the first time. Trading conditions in the offshore market were further strained by the incentive this discount provided for RMB to flow back onshore to take advantage of a stronger onshore rate.

3.3.2 *Literature Review*

Although the rise of the Chinese currency is more present in the current debate of the future global currency structure than ever before the Chinese FX regime still seems like a Gordian knot with respect to forecast performance. For decades gaining insights in the FX markets and improving the forecasting performance has been in the center of attention of many academics as well as financial market professionals. On the one hand the performance of professional forecasters has always been subject to a lot of critique. Recently, **?** showed that exchange rates follow a martingale process at short horizons, but over long horizons are less likely to follow a random process and may contain some predictable structure. Conversely, forecasting models do not perform better than simple naïve forecasts.

One of the first steps in forecasting exchange rates is to identify the underlying exchange regime. In general, international financial markets as a whole do not follow at all a one size fits all approach. This is especially true for FX markets where the underlying regimes change over the course of time as well as from country to country. For example Frankel (1999) roughly classified exchange rate regimes to be in the flexible corner, to be intermediate or in the fixed corner respectively. In this paper I focus on one special case of an intermediate exchange regime which is to some extent similar to what for example Calvo and Reinhart (2002) characterized as soft peg.

Whalley and Chen (2013) discussed whether the CNH should be seen as a so-called stepping stone to full convertibility or as a workaround (internationalization without convertibility) and also give a very good overview of the two RMB markets. Under the expression "RMB market" one can subsume a substantial variety of financial market products whereas onshore products are traded in CNY and offshore products are traded in CNH, i.e. spot trading, forward products, interest rate and also cross currency products. Ding et al. (2012) pointed out the starting point of offshore trading has been marked by the PBOC in July 2010. Before that point in time the main focus of attention with subject to Chinese exchange rates has been on the market for non-deliverable forwards (NDF). Amongst others, Colavecchio and Funke (2008) analyzed the impact of volatility spill-overs from the Chinese NDF market on several Asia-Pacific markets using multivariate GARCH techniques. They found out that Chinese NDFs in fact had impacts on China's trading partners' currencies. But these impacts did vary to a large extend due to different financial integration.

Currently the focus of the financial industry and that of a growing of amount academic researchers is on China's offshore markets with Hong Kong being the most important and best developed. The Hong Kong market - often referred to as mainland China's test vehicle for free trade of the Chinese currency as well as bonds denominated in RMB (see for example Fung and Yau (2012)) - has also been highlighted in the People's Republic's most recent five-year plan. According to Fung and Yau the state planners want the offshore market of the special administrative region to support the RMB in becoming an international currency. Having the same currency RMB being traded in three different markets - onshore, offshore and NDF - raises inevitably the questions of parity.

Besides, the offshore RMB bond market was developed as part of China's attempt to internationalize the RMB. It enhances the circulation of RMB outside mainland China. Loechel et al. (2013) focused on forecasting the term structure of yields in Chinese government bond market. Their paper aims to identify the determinants of the Hong Kong offshore sovereign yield curve and to test the hypothesis that, other than its onshore equivalent, the respective offshore curve is not predominantly driven by policy-related factors. They found that onshore government bond yields are primarily driven by policy-related factors such as the policy rate and money supply, whereas offshore government bond yields are additionally driven by market-related factors as well as liquidity constraints. At the current stage of market development there are virtually no spillover effects between the onshore and offshore government bond curves.

3.3.3 *Methodology and Implementation*

Research formulation

The main goal of paper C is to gain insights in the comparatively new market for offshore RMB (CNH spot market) and to detect first indications for feasible forecasting models for the onshore RMB (CNY spot market) respectively to improve CNY spot forecasts. I employ a simple GARCH model as well as neural networks. I do also analyze the somewhat older NDF market for RMB for which for example Ding et al. (2012) found a strong relationship with the CNY spot rate. As their work deals with the three RMB markets until June 2011 and since then the CNH market grew quite rapidly and seems to be replacing the NDF market, I lay my main focus on the CNH market.

Data object

I collect daily exchange rate data for onshore spot (CNY), offshore spot (CNH), one-month offshore NDF and CNH forward rates from Bloomberg. Although some studies argue in favour of longer NDF maturities, I use one-month rates given one-month NDFs are less prone to purely speculative pressures, more liquid, and less susceptible to exaggerated price swings. My sample period spans 08 September 2010 to 20 March 2013. Figure 3.5a shows data points of the mentioned series.

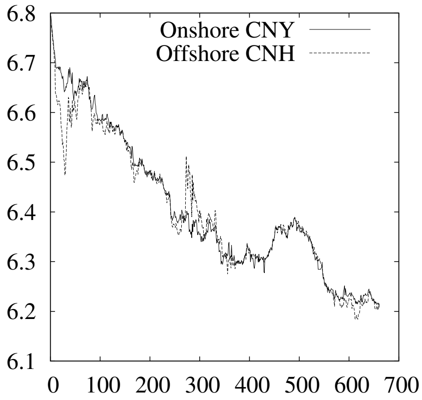
Implementation

For purpose of forecasting, I conduct a rolling-window technique of 100 data points to generate one step-ahead forecasts. The first insample runs from 08 September 2010 to 25 January 2011. The insample subset is used to estimate the statistical models and identify the neural network structure while the second is used for independent out-of-sample prediction comparison. This implies that I get a sample of 560 daily observations for the one step-ahead forecasting period.

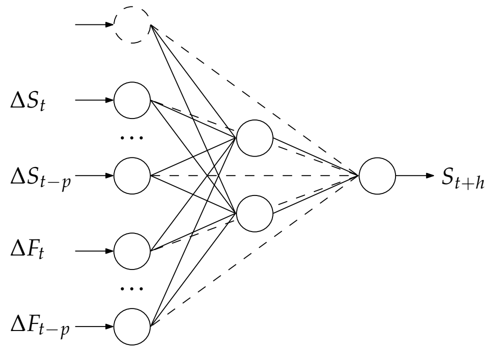
Model specification

I separate all results in univariate and multivariate classes: The univariate models consist of single series of CNY, CNH and their spread. I exclusively analyze the CNY in a multivariate way by incorporation of the one-month forward rates NDF and CNH respectively.

Figure 3.5: Examined FX rates and neural network specification



(a) Onshore/offshore spot rates



(b) Multivariate network specification for spot rate forecasting

Evaluation

The forecast performance of each model is assessed using the conventional Root Mean Square Error metric (RMSE) and Theil's U statistic. The latter allows a relative comparison of formal forecasting methods with a naïve model, a no-change Random Walk (RW). Statistical performance measures are often inappropriate for financial applications. Trading strategies guided by forecasts on the direction of price change may be more effective and generate higher profits. Therefore, predicting the direction is a practical issue which usually affects a financial trader's decision to buy or sell a contract. The trading simulation assumes that, at the beginning of each trading day, the investor will invest 1 monetary unit at the beginning of each contract period.

3.3.4 *Empirical Findings*

In this paper, I have examined the influence of the offshore CNH trading on onshore RMB rates (CNY). In contrast to prior studies I assume that the new CNH trading market becomes more relevant for the onshore CNY. Thus, I expect a tendency for parity between these two rates. To proof my assumption I predict single CNH and CNY rates, as well as multivariate effects of forward rates on the CNY with a GARCH-type and a neural network model.

- It is remarkable that predicting the spread is more difficult than the offshore CNH or onshore CNY. For the spread-behaviour I conclude that both markets still have a moderate level of comovement. Thus, there might exists a low level of information integration between CNY and CNH rates.

- When examining onshore spot trading against offshore NDF trading, my results show no ambiguous picture that onshore spot rates are influenced by offshore forward rates. This is not in line with prior results, where the CNY and NDF markets became even more informatively integrated after the CNH began trading.

- While the NDF is a contract whose forward curve acts like a futures curve on onshore Yuan spot rates, the CNH is a spot rate whose forward curve acts more like an onshore interest rate curve. Thus, NDF rates more closely track onshore Yuan spot rates whereas CNH rates more closely track onshore interest rates.

- My results do not support my assumption of a parity between the CNY and CNH. On the one hand the fact that the used forecasting methods do not outperform the naïve RW forecasts points to the direction that the price movements in the Chinese FX markets are similar to the movements in developed economies' FX markets, which are said to be rather efficient. On the other hand I found strong evidence that structural breaks do exist in the RMB markets.

In summary, my results give us no ambiguous evidence to confirm my assumption. Having in mind that the CNH market is rather new and subject to a lot of regulatory changes within a short time frame this is not surprising at all. The paradox lies in the fact that from a forecasting perspective Chinese FX market seem to be rather effective although substantial capital controls do exist. Nevertheless, several extensions for further research are necessary. From my point of view further research should focus on structural breaks and much more advanced forecasting methods. First, I would incorporate statistical multivariate GARCH models to analyze the relationship between the CNH market and CNY rates in detail. I would expect to get practical hints for a better specification of FAUN to improve forecast accuracy.

4

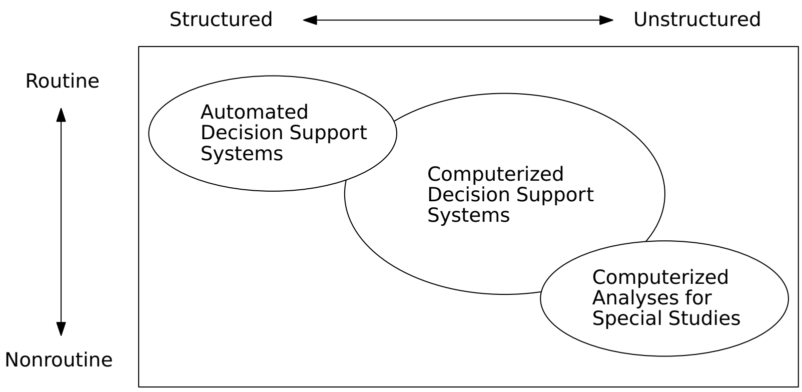
DECISION MAKING TECHNIQUES

4.1 MODEL-DRIVEN DECISION SUPPORT SYSTEMS FOR TRADING

Any capability to approximate market price functions or forecasting time series data leads to strategic advantages, which may be the key to success in financial institutions. In real life, one would be interested not only in efforts in forecasting, but also in practical trading strategies with possibility of taking positions in various financial markets. Nowadays, the prominence of sophisticated mathematical financial models in use and the rapidly expanding data sets involved, and the potential for catastrophic losses contribute to the high relevance of DSS in the finance.

At first decision support researchers need to differentiate three computerized systems associated with improving or enhancing individual and organizational decision making as shown in figure 4.1.

Figure 4.1: Different computerized DSSs; Power and Sharda (2007)



Automated decision systems are intended to automate and make decisions in routine, well-structured situations, whereas DSSs are auxiliary systems intended to assist decision makers in a wide variety of semi-structured and recurring decision situations. Finally, computerized tools used by technical experts to complete special decision studies are usually not appropriately categorized as DSSs. In this chapter I will put the attention on the automated - or model-driven - DSS fitted with neural networks embedded in high-frequency trading systems.

Financial markets are undergoing rapid innovation due to the continuing proliferation of computer power and algorithms. These developments have created a new discipline called algorithmic trading and high-frequency trading. Algorithmic trading or automated trading, is the use of electronic platforms for entering trading orders with an algorithm which executes pre-programmed trading instructions whose variables may include timing, price, or quantity of the order, or in many cases initiating the order by a robot, without human intervention. A special class of algorithmic trading is HFT.

HFT strategies utilize computers that make elaborate decisions to initiate orders based on information that is received electronically, before human traders are capable of processing the information they observe. Thus, HFT strategies are characterized by a higher number of trades and a lower average gain per trade. Traders execute multiple trades each day, gaining a fraction of percent return per trade, with few, if any, positions carried overnight.

The advances in computer technology over the past decades have enabled fully automated high-frequency trading. Technological innovation has always been a driving factor in the development of algorithmic trading and HFT. Beside the automation of financial markets, the use of computer algorithms to support trading decisions or even to make independent trading decisions has become commonplace. The competitive edge has become an issue of speed and sophistication of algorithms. Computational trading application must accomplish the following tasks:

- Automated trading signals,
- Auto-hedging,
- Risk allocation algorithm,
- Pricing and
- Execution engines.

To be more specific, efficient high-frequency trading systems make a full range of decisions, from identification of underpriced or overpriced options, through optimal portfolio allocation, to best execution. A signal must be precise enough to trigger trades in a fraction of a second.

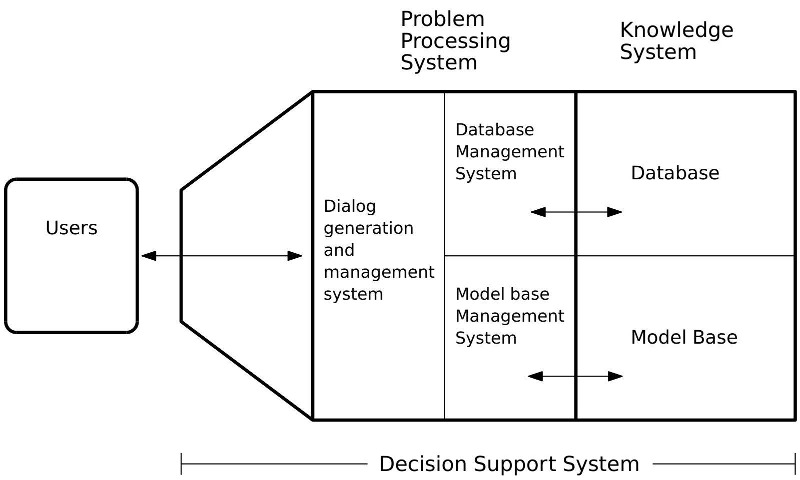
Of course, today's algorithmic trading involves neural networks, fuzzy logic, pattern recognition. Network-based models may be particularly valuable if the decision contains important non-linear elements or some of the other advantages of neural networks are crucial in a given application. For example if one believes that a group of indicators are somehow indicative of a change in price for a trading instrument but one does not have any rules in mind, one may use those indicators in a neural network to achieve a precise trading signal.

4.2 HIGH-FREQUENCY TRADING SYSTEMS WITH NEURAL COMPUTATION

4.2.1 *Literature Review*

Holsapple (2008) defined a decision support system simply as any system that represents and processes information for the purpose of improving decision making. Such systems are used by decision makers by using both a large data bases and a model base as shown in figure 4.2. According to Power and Sharda (2007), many technologies have been used to support decision making, and thus constitute DSS. Zhang et al. (2009) defined financial DSS as system which help decision makers solve problems within the financial management domain. Weber (2008) asserted that the role of DSS in the decision process can be either leading to a clear and unique best solution (normative) or providing information and guidance to the decision (decision-analytic). He pointed out that the core elements of a DSS are the same as any DSS: a data base, a model base, and a user interface. These core components are also evident in the more comprehensive DSS framework proposed by Zhang et al. (2009).

Figure 4.2: DSS architecture framework; Holsapple (2008)



Considering the evolution of non-linear dynamic systems to improve decisions is certainly not a new idea. There is a wide range of research in context of model-driven DSS, e.g. Gupta (2006), Turban et al. (2010), Grosan and Abraham (2011) and Schuff et al. (2011). Beraldi et al. (2011) presented a DSS which implements sophisticated mathematical models and integrates simulation and optimization techniques. Today, DSSs use interactive and artificial intelligence computer-based systems like neural networks for decision making. Artificial intelligence programs often learn from a priori given processes, data, etc. and corresponding appropriate decisions.

While algorithmic trading is defined by Hendershott et al. (2011) as "the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission", HFT remains undefined, but it is considered as a subcategory of algorithmic trading and includes more sophisticated and complex strategies that make use of the fast connection and processing speed of computers. According to Aldridge (2010), high-frequency is defined as quantitative analysis embedded in computer systems processing data and making trading decisions at high speeds and keeping no positions overnight.

4.2.2 *Methodology and Implementation*

Research formulation

In paper D I present steps towards a model-driven financial decision support model to pricing option on currency futures, which can be embedded in a high-frequency trading process. To develop an appropriate DSS, I use the design science methodology of Hevner et al. (2004). This leads to three major challenges:

1. Decision problem: Financial trading systems need support in making correct trading decisions, which are rather complex but important for participants in financial markets.
2. Option pricing problem: An accurate market valuation of option products in the FX market is still difficult and needs appropriate models and techniques.
3. Performance problem: From the operational perspective, the high speed of computer-driven decisions requires a particular comfort level with computer-driven execution.

Model framework

Most systematic trading platforms are organized as shown in figure 4.2. A successful high-frequency trading system adapts itself easily to contemporary market conditions. As a result, most high-frequency systems accept, process, and archive volumes of quotes and other market data delivered at real-time frequency. Some systems may convert streaming real-time data into equally spaced data intervals for use in their internal econometric analysis. Other systems may run on the raw, irregularly spaced quotes. The decision whether to convert the data should be based on the requirements of the run-time econometric analysis.

Data and implementation

I propose a heuristic option pricing model with FAUN to synthesize the option premium for all call FX option. I also implement FAUN as a core engine in a high-frequency trading process. To evaluate its usability I start an experimental design with empirical tick data of EUR/USD options on currency futures. The raw data set is the same as used in paper B and paper E, but here I concentrated more on insample training large tick data without any out-of-sample intervals.

Evaluation

I identify problem relevance in the field of pricing options in financial markets, and suggest needs for efficient DSS to manage high-frequency trading processes. I perform my network training with the FAUN neurosimulator. The FAUN neurosimulator uses fine-grained parallelization which allows easily achieved speedups on dual and quad core Central Processing Unit (CPU)s. FAUN also features coarse-grained parallelization using an easy to install grid computing client. It is possible to use clusters of heterogeneous workstations. Furthermore, using reverse accumulation and matrix algorithms allow a very efficient computation. This technical specifications make FAUN suitable for HFT, where computational requirements should be high and require special high performance computers.

4.3 EMPIRICAL FINDINGS

The results are encouraging in the sense that FAUN provides accurate market prices for six different strike prices simultaneously. If the market and heuristic prices differ significantly a trader can take this as a signal that an option is currently either too cheap or too expensive. I am now able to answer the research formulation in the following way:

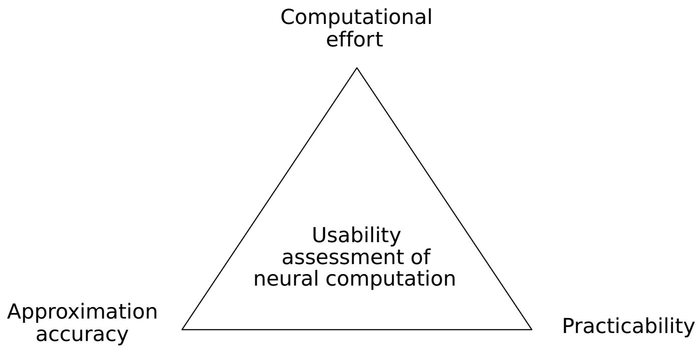
- Neural networks are a suitable core engine for a model-driven DSS embedded in a high-frequency trading process and can support trading decisions.
- Run-time evaluation of ensembles takes fractions of a second and is therefore instantaneous in a high-frequency context.
- Contrarily, post-trade network training is a computing-intensive issue.

From my point of view the most developable aspect is to test the model on a wider range of overlapping option series with different expiry dates. This will allow us to better gauge the practical applicability of FAUN. The proposed methodology and design of a network-based HFT trading system might evaluated as proposed in Paper B.

5
CRITICAL ASSESSMENT AND LIMITATIONS

In evaluating the empirical studies, there are still some questions left: first, can the empirical results be generalized? Second, are there any restrictions to a practical implementation, which have not been taken into account? An evaluation should be developed on the basis of some major criteria. For this purpose, I have identified three assessment criteria as shown in figure 5.1. I will give answers to the two questions mentioned above in this chapter.

Figure 5.1: Assessment criteria



APPROXIMATION ACCURACY

Artificial neural networks, as a semi-parametric data-driven approach, have been proposed as an alternative approximation technique, which includes market price synthesis and forecasting of time series. The popularity of neural networks as a generalized non-linear forecasting model is due to several distinguishing features that make them a valuable and attractive tool for approximation purposes. Neural networks as an universal approximator, as explained earlier, appear to be particularly suitable for financial time series approximation for a number of reasons:

- They are reliable for modeling non-linear, complex and dynamic market signals. They are capable to perform non-linear modeling without an a priori knowledge about the relationships between input and outputs variables.

- They can perform prediction after learning the underlying relationship between the input variables and outputs.
- One of the major advantages of neural networks is their ability to generalize. This means that a trained network could classify data from the same class as the learning data that it has never seen before.
- They are self-adaptive methods, i.e. numerical parameters are tuned by a learning algorithm.
- They do not require any assumptions concerning the underlying data-generating process and can handle noisy data.

From a statistician's point of view, neural networks are analogous to nonparametric, non-linear regression models. But, it is not a panacea, because the basic principle, the minimization of an error, resembles a simple regression.

Nevertheless, one can assess the value of my empirical computations with FAUN and other benchmark models by two criteria:

1. Effectiveness of validation and
2. Effectiveness of implementation.

First, effectiveness of validation ensures that the insample or out-of-sample procedure is well specified. This includes comparisons with well-accepted models, use of ex-ante validations and use of a reasonable sample of forecasts, i.e. the size of the validation samples should be adequate to allow inferences to be drawn. It is important to note, that a comparison with closed-form benchmark models is not always informative. In both cases, forecasting and option pricing, one can control performance results by model settings. Hence, many authors choose a constant volatility estimator for their benchmark option pricing model. But it is well known, that this parameter effects significantly the pricing performance. I made the experience that out-of-sample pricing in very short intervals, like the 15 minutes buckets in Paper B, leads to a perfect specified closed-form model.

In addition, Hanke (1999) applied neural networks and the BS model to European-style call options on the DAX index. After optimizing the volatility and interest rate data to suit the BS model, the neural network was less accurate than BS. Thus, it is not obvious, that my neural network specification outperforms the closed-form model in general. The results depend on the given data set and model specification. There exist no exact methods for finding the "right" inputs or the "right" network topology: Practitioners have to use heuristics until they arrive at a combination of inputs and topology that satisfies their requirements. However, this is also a general statement of the universal approximation theorem.

Second, for studies that have effectively validated the neural network one demand effectiveness of implementation. In determining the effectiveness with which a neural network had been developed and tested, I used the guidelines for evaluating network performance suggested by Refenes (1995):

- Convergence is concerned with the problem of whether the learning procedure is capable of learning the classification defined in a data set. In evaluating this criterion, therefore, one was interested in the insample performance of the proposed network since it determines the network's convergence capability and sets a benchmark for assessing the generalizabilty, i.e. ex ante performance, of the network.

- Generalization measures the ability of neural networks to recognize patterns outside the training sample. The accuracy rates achieved during the learning phase typically define the bounds for generalization. If performance on a new sample is similar to that in the convergence phase, the neural network is considered to have learned well.

- Stability is the consistency of results, during the validation phase, with different samples of data. This criterion evaluates whether the neural network configuration determined during the learning phase and the results of the generalization phase are consistent across different samples of test data. Studies could demonstrate stability either through use of iterative resampling from the same data set or by using multiple samples for training and validation.

The criteria are sufficiently general to be applicable to any network architecture or learning mechanism. If one wishes to use empirical studies to make a case for or against the applicability of neural networks to forecasting or prediction, though, one must be able to determine which represents good implementations for that purpose. Convergence problems occurs mostly in case of deriving partial derivatives. While closed-form approaches bound some derivatives in a particular interval, e.g. Δ of a call option in $[0, 1]$, the neural network does not inherently know these interval boundary. A solution for this problem might be to specify alternative network topologies by replacing the target option price by the desired hedge ratio proxy. Carverhill and Cheuk (2003) reported a better performance by training the networks based on the performance criterion ultimately used. The reason is that the neural network minimizes the error of the price function, but has no knowledge of the unobservable sensitivity.

PRACTICABILITY

Performing a permanently run-time network-based DSS put high requirements on practicality and useability. Encouraging empirical results are only one side of the coin - but neural networks must also prove in practical use as robust and stable. They compete with conventional closed-form analytical approaches in the field of market price synthesis and statistical models in time series analysis. For both my study and in general, the following limitations may be mentioned:

- Neural network methodology and modeling techniques are rapidly changing, whereas many statistical modeling techniques are stable and well developed.

- Software is readily available for statistical techniques but commercial artificial neural network software, although of good quality, often lags developments in the field.
- Neural network models are harder to interpret than many other statistical models.
- Neural networks contain more parameters to estimate than most other statistical forecasting models do; this can result in overfitting problems. Moreover, they require a large diversity of training for real-world operation.
- Though the estimation procedure can be automated, neural networks must be re-estimated periodically when new data arrives.

One can extract two major requirements from the listed points: robustness and stability; i.e. are the network results of its term, in other market conditions stable? Is there much manual adjustment needed?

According to chapter 2, I have seen some weak points of neural networks during my computations in the field of market price synthesis. On the one hand, analytical approaches such as the Black model are easy to use, and they produce very quickly desired results with sufficient accuracy. On the other side, FAUN underperforms closed-form models in this data regions, due to the lack of data. Thus, in case of less market liquidity, which results in less data points, network results mostly achieve higher deviations than benchmark models. Hence, the data dependency is a major disadvantage in the network performance evaluation. To avoid the problem of limited data for training - in my case OTM options - I have performed a modular network topology like those proposed by Gradojevic et al. (2009). The pricing function is decomposed into separate non-linearities called modules. The modules are trained independently on the data for the ITM and OTM options and during run-time pricing. Of course, the training error decreases, but induces an increased modeling effort.

Moreover, the model specification of neural networks in context of time series analysis is often difficult. While a number of tests and diagnostic tools help to specify conventional statistical models, neural networks models are usually specified by heuristic approaches. In this respect I can confirm Horniks presumption that poor results must arise from inadequate specification.

COMPUTATIONAL EFFORTS

Efficient implementation of trading algorithms is crucial, because a vast amount of data has to be processed in a very short time. A common criticism of neural networks, is that they require a large diversity of training data and operations. This is not surprising, since any learning machine needs sufficient representative examples in order to capture the underlying structure that allows it to generalize to new cases. These issues are common in neural networks that must decide from amongst a wide variety of responses, but can be dealt with in several ways, for example by randomly shuffling the training examples, by using a numerical optimization algorithm.

To implement large and effective software neural networks, much processing and storage resources need to be committed. Neural network systems will often need to simulate the transmission of signals through many of these connections and their associated neurons - which must often be matched with incredible amounts of CPU processing power and time. While neural networks often yield effective programs, they too often do so at the cost of efficiency.

In response to this kind of criticism, one should note that although researchers involved in exploring learning algorithms for neural networks are gradually uncovering generic principles which allow a learning machine to be successful. For that matter, the following high-performance computing approaches are available:

- Parallel calculations: Parallel calculations can be split into many smaller sub-calculations. This means that each sub-calculation can be worked on by a different processor, so that many sub-calculations can be worked on "in parallel". This allows ones to speed up computations.

- Coarse-grained calculations: Coarse-grained calculations are often embarrassingly parallel. A calculation is embarrassingly parallel when each sub-calculation is independent of all the other calculations.

- Fine-grained calculations: In a fine-grained calculation, each sub-calculation is dependent on the result of another sub-calculation. Fine-grained parallel calculations require very clever programming to make the most of their parallelism, so that the right information is available to processors at the right time.

- Grid computing: Many interesting problems in science require a combination of fine- and coarse-grained calculations, and this is where grids can be particularly powerful.

For example, in the case of financial modeling, one launch many similar calculations to see how different parameters affect their models. Each calculation is a fine-grained parallel calculation that needs to run on a single cluster or supercomputer. Using a grid, these many independent calculations can be distributed over many different grid clusters, thus adding coarse-grained parallelism and saving a lot of time.

In addition, since a neural network requires a considerable number of vector and matrix operations to get results, it is very suitable to be implemented in a parallel programming model and run on Graphics Processing Unit (GPU). A GPU offers a highly parallelized computing architecture that is suitable for massive parallel computing tasks. Unlike modern CPU, which have two or more cores, a modern GPU has hundreds of cores that provide an incredible computational platform for a wide variety of tasks. The recent resurgence of interest in neural networks owes a certain debt to the availability of affordable, powerful GPU which routinely speed up common operations such as large matrix computations.

FUTURE RESEARCH

Throughout this dissertation I have attempted to provide empirical evidence for neural network's capability to approximate financial time series. The elaborated limitations give me useful hints for further research.

First, to demonstrate the universality of this study's results, it is necessary to validate specified models against a broader data base. To check the robustness and stability of network-based approximations I recommend to perform monte-carlo methods. These methods can simulate a lot of different market situations and time series data. Of course, the simulated data is artificial. But it allows a deeper analysis of network behavior. Moreover, one should also take real time series into account.

Second, I have only used MLPs in my empirical investigations. Implementing other network topologies and neural network types like recurrent networks, genetic algorithms or radial basis function networks are alternative models, which could achieve better results.

Third, I would expect that an incorporation of more effective and modern computational methods improve the computation performance. This is an important fact in order to confirm a practical and routinely implementation. Nevertheless, the latter point needs programming knowledge, time … and money.

6 CONCLUSION

This thesis seeks to address how neural networks may be put to work for more accurate approximation and for better decision making in financial markets. I perform several different empirical studies to investigate the approximation capability of neural networks in case of time series analysis and market price synthesis. For empirical analysis I use the FAUN neurosimulator.

The universal approximation theorem of Cybenko (1989) and Hornik (1989) provides the latent basis of my empirical studies. Artificial neural networks can be mathematically shown to be universal function approximators. This means that neural networks can automatically approximate whatever functional form best characterizes the data. Since it is my goal to extract an alternative option pricing function by market observations, I focus on the MLP that are applicable to non-linear regression problems.

In order to study its approximation ability for computational economics, I perform different empirical computations. First, due to their complex and non-linear character, neural networks are suitable for approximating price functions of financial options. In a more heuristic approach financial market actors are able to approximate network-based pricing formulas and their partial derivatives depending on specific market situations. I present empirical results for pricing and hedging Foreign exchange (FX) options, which confirm the capability of neural networks for universal approximation.

Second, real-time pricing and hedging algorithms market actors are interested in dynamics and predictions of relevant market variables. This leads to examination of autoregressive time series processes and model specifications with lagged input variables. I investigate the usage of neural computing for forecasting financial time series, where neural networks compete with conventional time series models. I show empirical studies about two financial markets: the maritime spot and derivatives freight rates market and the Chinese FX market. Neural networks achieve suitable results in both markets, which both have their own uniqueness.

Above all mentioned techniques remains the question of neuronal computing application in the financial industry. In a last step I thus propose the implementation and design of a financial decision support system with neural networks, which is a more business informatics oriented discussion. The merits of neural networks especially for high-dimensional problems are shown.

In summary, I have attempted to provide empirical evidence for neural network's capability to approximate financial time series. Main contributions are:

- Model option prices derived from neural networks can synthesize HFT option market prices in a similar manner, but in a simultaneous way and with a more parsimonious input specification. There is e.g. no need of volatility or interest estimation.
- If market liquidity exists, which is equivalent to full data availability in a particular state space, learning networks are capable to approximate first- and higher-order partial derivatives with a sufficient accuracy. But the approximation accuracy decreases with higher-order partial derivatives.
- However, I can not confirm the hypothesis that once a predominant network approximation is found for pricing purposes, the same could be applied for hedging. I have to notice that it is an exhausting balancing act for learning systems to apply the delivered pricing approximation function on unknown hedge parameters.
- In case of forecasting financial time series neural network results are comparable to those of the other models. Some regularities from two different financial markets:
- Tanker freight rates: Changes in spot rates are explained by autocorrelation and by changes in the forward rates; but: changes in forward rates are not explained by past changes in spot rates. There is, however, a highly significant autocorrelation in forward rates that is difficult to conciliate with efficient markets. These results imply that the futures prices contain valuable information about future spot rates.
- Renminbi: The results do not support our assumption of a parity between the CNY and CNH. On the one hand the fact that the used forecasting methods do not outperform the naïve RW forecasts points to the direction that the price movements in the Chinese FX markets are similar to the movements in developed economies' FX markets, which are said to be rather efficient. On the other hand I found strong evidence that structural breaks do exist in the RMB markets.
- Neural networks are a suitable core engine for a model-driven FDSS embedded in a high-frequency trading process and can support trading decisions.

Hence, this dissertation provides empirical evidence that neural networks are well suited for non-linear relations due to their ability to approximate any measurable function up to an arbitrary degree of accuracy. I also expose limitations and further research topics in doing with neural networks, which could improve neural networks applications in computational economics in the future.

Nevertheless, when I refer to the quote of Jules Verne at the beginning of this work, namely that small error steps lead to the truth, . . . then neural networks seem to approximate very well the truth.

Part II

APPENDED PAPERS

In the following part I append all my research contributions and papers. All papers are sorted by the proposed order of the publication chapter. Note that the nomenclature may vary in each paper.

A
THE »GREEKS APPROXIMATION« PAPER

Numerical Approximation of Option Pricing Functions and Its Partial Derivatives by Neural Networks

Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2013). *Numerical Approximation of Option Pricing Functions and Its Partial Derivatives by Neural Networks*. In: Dunis, C., Mettenheim, H.-J.v. and McGroarty, F. (Eds.), *New Developments in Quantitative Trading and Investment* (submitted/forthcoming). Palgrave Macmillan, Basingstoke.

ABSTRACT

This article presents a simple approach for numerical approximating the value and its partial derivatives of American call options by powerful neural networks. The key to this approach is the use of a parsimonious semi-parametric learning networks in order to approximate not only the option price but also their partial derivatives. We perform a empirical simulation with thousand of option prices derived by a simulation experiment. We show that the approximated pricing function of learning networks is suitable for generating fast run-time option pricing and hedging evaluation. Whereas neural networks can approximate desired functions in an appropriate manner, we show that approximation accuracy highly depends on market liquidity and decreases for higher-order derivatives. However, directly networking training on approximated observable Greeks reverse this failure.

KEYWORDS

American Call Option, Partial Derivatives, Greeks, Numerical Approximation, Neural Networks

JEL C45, C52, C61, C63, G12

Numerical Approximation of Option Pricing Functions and Its Partial Derivatives by Neural Networks

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1 INTRODUCTION

Option pricing models are among the most popular analytical methods for the solution of partial differential equations governing many problems in financial engineering. Due to a lack of closed-form solutions to American option valuation problems, a vast array of approximation schemes has been advanced. Numerical methods such as the finite difference method of Brennan and Schwartz (1977) and the binomial tree model of Cox et al. (1979) are among the earliest and still widely used ones. Even though these methods are quite flexible, they are also among the most time consuming ones.

Another category of potential methods includes analytical approximations. MacMillan (1986), Barone-Adesi and Whaley (1987) and Bjerksund and Stensland (1993) are among these methods. A common feature of these methods is that they are many times faster, but a drawback is that they are not very accurate, especially for long maturity options.

In absence of any closed form formula for American options, a reliable analytical approximation is obviously highly desirable. Network-based models are fundamentally different in some respects to theoretical models. First, since they do not rely on restrictive parametric assumptions such as lognormality or sample-path continuity. Second, they are adaptive and respond to structural changes in the data-generating processes and robust to specification errors that plague parametric models. Standard applications of neural networks (NN) do not involve any financial theory and can be used to estimate directly the unknown empirical option pricing function. As option pricing theory typically derives non-linear relations between an option price and the variables determining it, NNs are well suited for this purpose due to their ability to approximate any measurable function up to an arbitrary degree of accuracy. When properly trained, the network synthesizes the (true) option pricing formula, which may be used in the same way that formulas obtained from the parametric pricing method are used. From a practical perspective NNs are well suited to parallel computing, which allows significant gains in computational speed and efficiency.

First attempts of market price approximation with NNs were made in the early 1990ies. Pioneers are Malliaris and Salchenberger (1993) and Hutchinson et al. (1994), who compared the performance of the BS model and NNs in pricing American-style call options. Many of these studies show that NN models are capable of approximating option pricing functions. In the following, Anders et al. (1998), Garcia and Gençay (2000), Amilon (2003) and Andreou et al. (2006) got similar encouraging results regarding European-style options. Whereas some studies only concentrated on pricing accuracy some authors also performed a Delta-hedging simulation in order to investigate the first partial derivative of network functions.

However, Andreou et al. (2010) noted some limitations in using NNs for option pricing. In particular, the use of standard NNs can deliver option prices that violate fundamental financial principles, e.g., irrational option values or hedging parameters. But on the other side, the universal approximation theorem of Cybenko (1989) and Hornik (1991) states that a feed-forward network with a single hidden layer containing a finite number of neurons is a universal approximator among continuous functions.

The objective of this paper is to report a numerical approximation of option pricing functions and their derivatives by NNs. The benefits of our NN technology as a kind of core engine allow both option sellers and buyers to approximate call option prices and hedging parameters across different strike prices simultaneously and with parsimonious input specification.

Contrary to prior studies we pose the following challenge: are NNs not only capable to approximate option prices, but also its first- and higher-order partial derivatives with a sufficient degree of accuracy? In addition, does this approach satisfy necessary convergence criteria? We perform a simulation experiment, in which NNs discover American call option prices when trained on Barone-Adesi and Whaley (BAW) call option prices. The derived approximation function is then used to derive various partial derivatives.

Partial derivatives of financial options, the so-called Greeks of option values, are vital tools in risk management. Each Greek measures the sensitivity of the value of a portfolio to a small change in a given underlying parameter, so that component risks may be treated in isolation, and the portfolio rebalanced accordingly to achieve a desired exposure.

The remaining of the paper is organized as follows. First, we introduce the unique approximation capability of NNs. In section 3 we explain the pricing functions of financial options and their partial derivatives, which we want to approximate by NNs. In section 4 we perform a numerical experiment with artificial derived option prices by a Monte-Carlo simulation. Theoretical derived option Greeks compete with NN approximations. The paper ends with a brief conclusion and summary of the results in section 5.

2 APPROXIMATION CAPABILITIES OF FEEDFORWARD NEURAL NETWORKS

2.1 *Approximation of Functions by the Multilayer Perceptron*

Neural Networks can be mathematically shown to be universal function approximators. This means that NNs can automatically approximate whatever functional form best characterizes the data. One of the first versions of the theorem was proved by Cybenko (1989) for sigmoid activation functions. Hornik (1991) showed that it is not the specific choice of the activation function, but rather the multilayer feedforward architecture itself which gives NNs the potential of being universal approximators.

Let $a(\cdot)$ be a nonconstant, bounded, and monotonically-increasing continuous function. Given any function f and $\varepsilon > 0$, there exists an integer M and real constants $\alpha_j, \beta_j \in \mathbb{R}, w_j \in \mathbb{R}^N$, where $j = 1, \ldots, M$ such that we may define:

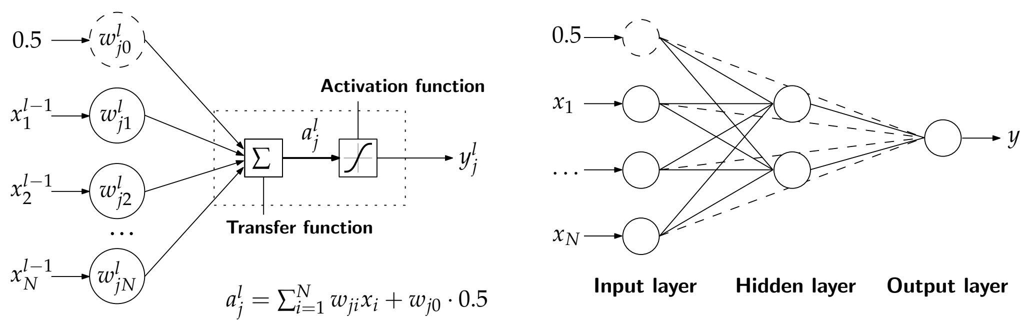
$$\hat{f}(x) := \sum_{j=1}^{M} \alpha_j a(w_j^{\mathsf{T}} x + \beta_j) \tag{A.1}$$

as an approximate realization of the function f, where f is independent of a; that is,

$$|f(x) - \hat{f}(x)| < \varepsilon. \tag{A.2}$$

Since it is our goal to extract an alternative option pricing function by market observations, we focus on multilayer perceptron (MLP) that are applicable to non-linear regression problems. We follow the argumentation of Hornik (1989), that feedforward networks with only one hidden layer and a linear output unit are able to approximate simultaneously its unknown derivatives up to an arbitrary degree of accuracy. This characteristic is substantial since the partial derivatives of a pricing formula are needed for the hedging of option positions.

Figure A.1: Exemplarily 3-layered perceptron



(a) Neuron j **(b)** Feedforward network

Referring to figure A.1, given an input $\vec{x}_i^{l-1}$ in layer $l-1$, a neuron j can compute an output y_j^l in layer l according to its prior training, represented by the weight vector $(w_{j0}^l, \vec{w}_j^{l\mathsf{T}})^\mathsf{T}$ where superscript T denotes the transpose operation. The weights provide the abilities of prediction or classification to the system. Firstly, the inputs $(\vec{x}_i^{l-1})$ fed to the input layer are weighted and summed up. Then they are entered to an activation function a_j^l in order to get an output from each neuron in the hidden layer. The weights are iteratively changed until the best loads are obtained. To find the right weights within a so-called training process thousands of multi-layer perceptrons with various topologies and with different weight initializations are trained.

Once a set of discrete data is available, the NN can be trained to approximate or generalize the function over the domain. NN training is commonly posed as an optimization problem in the weight space. The nonlinear least squares objective function in this case is defined by

$$\mathbb{E}(\vec{W}) = \sum_{p=1}^{I_t} e_p^2, \tag{A.3}$$

where I_t is the number of training patterns and

$$\varepsilon_p^2 = \left(f(\vec{x}_p) - \hat{f}(\vec{x}_p)\right)^2 \tag{A.4}$$

is the squared error associated with the training pattern p, f is the target or desired output, and $\hat{f}$ is the computed output corresponding to the input $\vec{x}_p$. The error vector is defined by

$$\vec{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{I_t})^\mathsf{T}. \tag{A.5}$$

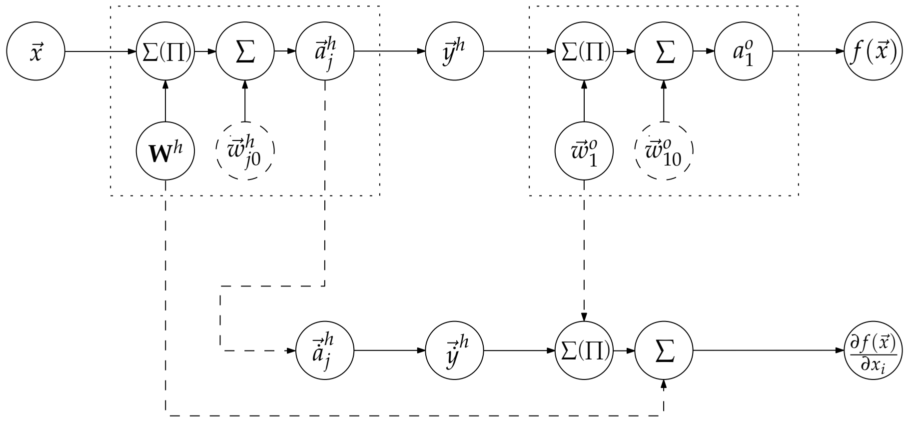
In the rest of this paper we only discuss three layer NN consisting of an input layer, a hidden layer and an output layer. Furthermore, we consider fully connected NNs in which a neuron will receive signals from each and every neuron in the immediately preceding layer.

2.2 *Numerical Approximation of Partial Derivatives*

The capability of NN with as few as one hidden layer to approximate functions has been theoretically proven by Hornik et al. (1990). Here, we are also interested in the numerical approximation of partial derivatives of functions. Fortunately, NN can be extended for this purpose as shown by Nguyen-Thien and Tran-Cong (1999). Figure A.2 describes an NN with a multi-neuron input layer, a single multi-neuron hidden layer and a single-neuron output layer.

The activation functions of the input layer neurons and output layer o neurons are simply the identify functions. On the other hand the tanh-sigmoidal function is

Figure A.2: Approximation of a function $f(\vec{x})$ and its first partial derivatives



A three-layer neural network for approximation of a function $f(\vec{x})$ and its first partial derivatives. Superscript h denotes the hidden layer and superscript o the output layer. Note that we have only one single neuron in the output layer, whose activation function a_1 retains the subscript 1 for consistency.

used by the hidden layer h neurons. This sigmoidal function and its derivative are given by

$$a_j^h(x) = \tanh x = \frac{1-e^{-2x}}{1+e^{-2x}}, \tag{A.6}$$

$$\dot{a}_j^h(x) = \frac{\mathrm{d}a_j^h(x)}{\mathrm{d}x} = 1 - \left(a_j^h(x)\right)^2 = \operatorname{sech}^2 x. \tag{A.7}$$

Thus, given an input $\vec{x} \in \mathbb{R}^N$, the function is computed by the network according to

$$\hat{f}(\vec{x}) = \sum_{j=1}^{M} w_{1j}^o a_j^h(\vec{x}^\top \vec{w}_j^h), \tag{A.8}$$

and the corresponding first order derivatives are given by

$$\frac{\partial \hat{f}(\vec{x})}{\partial x_i} = \sum_{j=1}^{M} w_{1j}^o w_{ji}^h \dot{a}_j^h(\vec{x}^\top \vec{w}_j^h), \quad i = 1,\ldots,N, \tag{A.9}$$

where M is the number of neurons in the hidden layer. We define the synaptic weight vector as

$$\vec{W} = \left(w_{10}^h, \vec{w}_1^{h\top}, \ldots, w_{M0}^h, \vec{w}_M^{h\top}, w_{10}^o, \vec{w}_1^{o\top}\right)^\top. \tag{A.10}$$

Note that biases $w_{k0}^h, k = 1,\ldots,M$ and w_{10}^o are also included. Second derivatives of the function can be derived as

$$\frac{\partial^2 \hat{f}(\vec{x})}{\partial x_i \partial x_k} = -2\sum_{j=1}^{M} w_{1j}^o w_{ji}^h w_{jk}^h \dot{a}_j^h(\vec{x}^\top \vec{w}_j^h) \cdot a_j^h(\vec{x}^\top \vec{w}_j^h), \quad i,k = 1,\ldots,N. \tag{A.11}$$

Thus, given an activation function such as equation (A.6), a nonlinear function can be approximated by equation (A.8). Once the network is trained successfully, the calculation of the function's first and second order partial derivatives is given by equations (A.9) and (A.11). It remains to determine the synaptic weight vector from a given set of data points. Note that the weight vector is not unique due the symmetry of fully connected NNs.

3 PRICE DERIVATIVES OF AMERICAN CALL OPTIONS

The problem of finding the price of an American option is related to the optimal stopping problem of finding the time to execute the option. Since the American option can be exercised at any time before the expiration date, the Black-Scholes equation becomes an inequality of the form

$$\frac{\partial C}{\partial t} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + rS\frac{\partial C}{\partial S} - rC \leq 0 \tag{A.12}$$

with the terminal and (free) boundary conditions: $C(S,T) = H(S)$ and $C(S,t) \geq H(S)$ where $H(S)$ denotes the payoff at asset price S. In general this inequality does not have a closed form solution.

Barone-Adesi and Whaley (1987) provide an analytical approximation formula, where the stochastic differential equation is split into two components: the European option value and the early exercise premium. With some assumptions, a quadratic equation that approximates the solution for the latter is then obtained. This solution involves finding the critical value, such that one is indifferent between early exercise and holding to maturity.

Bjerksund and Stensland (1993) provide an approximation based on an exercise strategy corresponding to a trigger price. Here, if the underlying asset price is greater than or equal to the trigger price it is optimal to exercise, and the value must equal $S - X$. This approximation is computationally inexpensive and the method is fast, with evidence indicating that the approximation may be more accurate in pricing long dated options than Barone-Adesi and Whaley.

In addition to finding accurate pricing methods for American options, traders are interested in pricing sensitives for hedging and speculative purposes. In mathematical finance, the Greeks are the quantities representing the sensitivity of the price of derivatives such as options to a change in underlying parameters on which the value of an instrument or portfolio of financial instruments is dependent. Collectively these have also been called the risk sensitivities, risk measures or hedge parameters.

For computational purposes we analyze the first, second and third partial derivatives. Since deriving partial derivatives depends on the input variables of our network model, derivatives with respect to r and σ are not possible. In summary, we choose the following Greeks in equations (A.13) to (A.17).

$$\text{Delta} \quad \Delta = \frac{\partial C}{\partial S} \tag{A.13}$$

$$\text{Dual Delta} \quad = \frac{\partial C}{\partial X} \tag{A.14}$$

$$\text{Theta} \quad \Theta = -\frac{\partial C}{\partial \tau} \tag{A.15}$$

$$\text{Gamma} \quad \Gamma = \frac{\partial \Delta}{\partial S} = \frac{\partial^2 C}{\partial S^2} \tag{A.16}$$

$$\text{Speed} \quad = \frac{\partial \Gamma}{\partial S} = \frac{\partial^3 C}{\partial S^3} \tag{A.17}$$

Delta, Δ, measures the rate of change of option value C with respect to changes in the underlying asset's price S. In addition, the correct, exact calculation for the probability of an option finishing in-the-money (ITM) is its Dual Delta, which is the first derivative of option price with respect to strike X.

Theta, Θ, measures the sensitivity of the value of the derivative to the passage of time (time decay). Theta is almost always negative for American long calls and puts. In summary, Delta, Dual Delta and Theta are first-order Greeks.

As a representee of second-order Greeks we compute Gamma, Γ, which measures the rate of change in the delta with respect to changes in the underlying price. Gamma is the second derivative of the value function with respect to the underlying price. All long options have positive gamma. Gamma is greatest approximately at-the-money (ATM) and diminishes the further out you go either ITM or out-of-the-money (OTM). Gamma is important because it corrects for the convexity of value. When a trader seeks to establish an effective Delta-hedge for a portfolio, the trader may also seek to neutralize the portfolio's Gamma, as this will ensure that the hedge will be effective over a wider range of underlying price movements.

The third-order Greek Speed measures the rate of change in Gamma with respect to changes in the underlying price. Speed is the third derivative of the value function with respect to the underlying spot price S. Speed can be important to monitor when Delta-hedging or Gamma-hedging a portfolio.

4 LEARNING GREEKS – A SIMULATION EXPERIMENT

4.1 *Calibrating the Simulation*

We can now outline the components of our simulation experiment. We generate a sample path of EUR/USD currency (FX) and option prices on which the learning networks are trained, i.e., the network parameters are fitted to the sample path so as to minimize a quadratic loss function. This yields a network pricing formula.

In the first phase of our simulation experiment - the training phase - we simulate a three-month sample of intra-day EUR/USD FX prices, and create a cross-section of options according to the rules used by the Chicago Mercantile Exchange (CME) with prices given by the BAW analytical approximation. We refer to this three-month sample of FX and (multiple) option prices as a single training path, since the network is trained on this sample. We assume that the underlying asset for our simulation experiments is a typical CME FX asset, with an initial price S(0) of 1.35, an annual continuously compounded expected rate of return μ of 2 percent, and an annual volatility σ of 10 percent. To run our simulation, we adopt a Black-Scholes framework. The price of the underlying asset on which the option is written follows a geometric Brownian motion:

$$dS(t) = \mu S(t)dt + \sigma S(t)dW(t)$$

and taking a time interval of four hours (six quotes per day), we draw 396 pseudo-random variates $Z(t)$ from the distribution $N(\mu \cdot dt, \sigma^2 \cdot dt)$ to obtain three-month of intra-day continuously compounded returns, which are converted to prices with the usual relations $S(t) = S(0)e^{\sum_{i=1}^{t} Z_i}, t \geq 0$. Assuming that the number of trading days per year is 252, the time increment dt between two quotes is 0.000661.

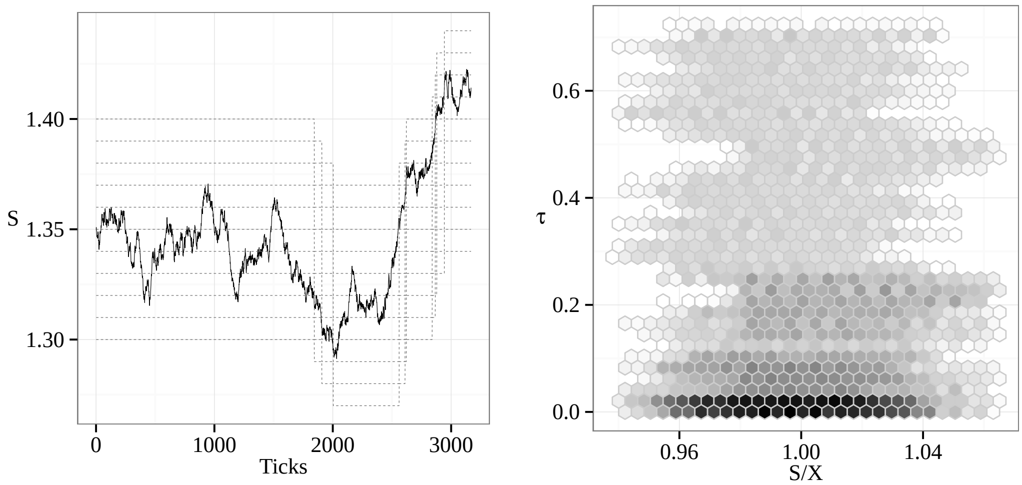
Given a simulated training path $\{S(t)\}$ of daily stock prices, we construct a corresponding path of option prices according to the rules of the CME for introducing options on stocks. At any one time, CME FX options outstanding on a particular currency have eight unique expiration dates: the current week, the current month, the next month, and the following four expirations from a quarterly schedule. The CME sets strike prices at multiples of 0.01 for EUR/USD. We set a grid of eleven strike prices around our starting point and move the grid in that way, into which all of our simulated prices fall. We assume that all of the options generated according to these rules are traded every day, although in practice, far-from the-money and long-dated options are often very illiquid.

Our simulated training path is shown in figure A.3a. We can also plot the training path as a three-dimensional surface if we normalize stock and option prices by the appropriate strike price and consider the option price as a function of the form $f(S/X, 1, \tau)$ (see figure A.4), where τ denotes the maturity time $T - t$. NN trains on available data, thus we visualize the data density space in figure A.3b. Not surprisingly the most data records occur in regions with lower maturity τ (black colored regions). The size in terms of number of options and total number of data points is about 20,790 quotes.

4.2 *Training Option Prices*

At this stage, we have to find the best topology in order to minimize the training and validation error. In general, this is achieved by comparing the best trained network in each simulation study. We choose five hidden neurons, which lead to accurate results while the computation time will be controllable. We test a parsimonious parameterized model, which relaxes the estimation of r and σ. According to Hutchinson et al. (1994), the approximated BAW call option price divided by the

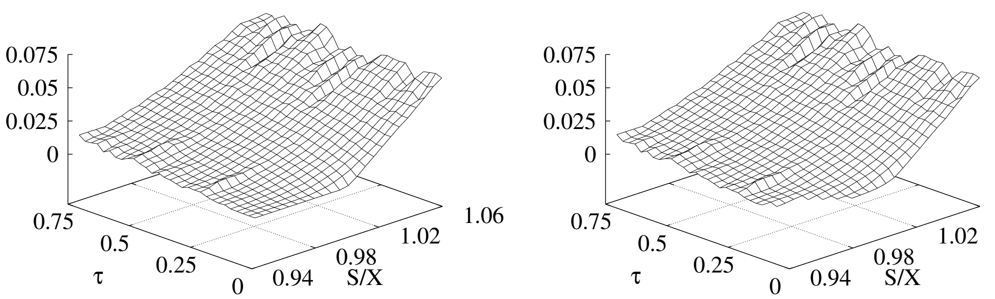
Figure A.3: Simulated training data of intra-day FX EUR/USD quotes



(a) Training path $\{S(t)\}$ **(b)** Option data density

strike price $\frac{C}{X}$ depends only on the permanently available moneyness $\frac{S}{X}$, which is the quotient of the underlying price S and the option's strike price X, and the time to expiration τ.

Figure A.4: Option call price approximation



(a) BAW call price $\frac{C}{X}$ **(b)** Network call price $\frac{\widehat{C}}{X}$

As we can see in figure A.4 this parsimonious specification with two input variables is capable to approximate the BAW call option price surface. The trained weights are shown in table A.1.

We perform several simulations with different network topologies and simulation steps to analyze error accuracy. Once an appropriate network has been found,

Table A.1: 2–5–1 NN results for BAW call price function[a]

	Hidden layer			Output layer	
Neuron j	w^h_{j0}	w^h_{j1}	w^h_{j2}	w^o_{1j}	w^o_{10}
1	-8.815885	2.924135	0.612804	5.784338	100.000000
2	4.677273	-0.240188	0.450100	-66.257553	
3	49.073833	7.451910	24.895050	0.265078	
4	-0.408146	-0.047813	0.181782	-100.000000	
5	10.937928	4.507884	6.313263	0.121390	

[a] There are two inputs and therefore the weights for the hidden layer are w^h_{ji} with $i = 0$ (bias), $i = 1, 2$. There is only one output and therefore the weights for the output layer are w^o_{10} (bias) and w^o_{1j}.

computing of option prices with this network takes fractions of a second. Hence, network evaluation is almost instantaneous even in a high-frequency context.

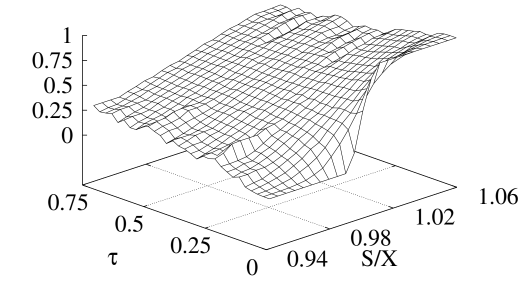
4.3 *Numerical Results*

In order to evaluate the approximation ratio, we exploit on the one hand visualizations to check the network behavior and on the other hand performance measures. Note that not only the approximation quality is crucial as particular convergence criteria must be strictly adhered to.

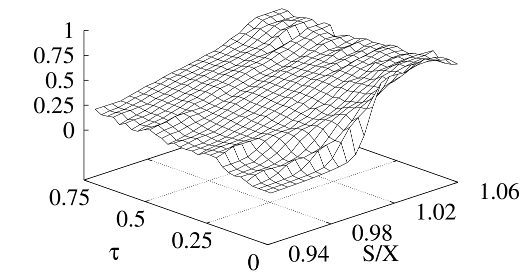
All partial derivatives are based on the approximated price function $\widehat{\frac{C}{X}}$. We can derive appropriate partial derivatives by analytically or numerically deriving the network functions, provided that the corresponding variable has been included as an input factor. In our case the partial derivatives with respect to S, X or *tau* can be carried out.

In figure A.5 we show the results for the first-order partial derivatives. For both S and X, we obtain a very encouraging approximation result and the convergence criteria is not violated. For theta, i.e., partially derived by the maturity, this is also true - but it is an exhausting balancing act for the NN to train the very few ATM options in the sensitive area exactly. It should be noted that most data space have values approaching zero.

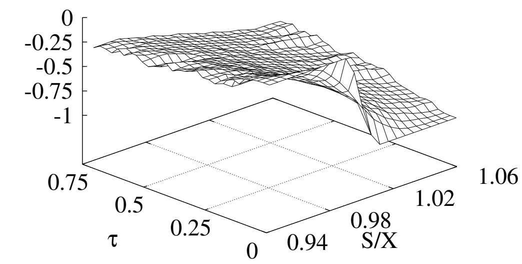
Figure A.5: First-order partial derivatives approximation



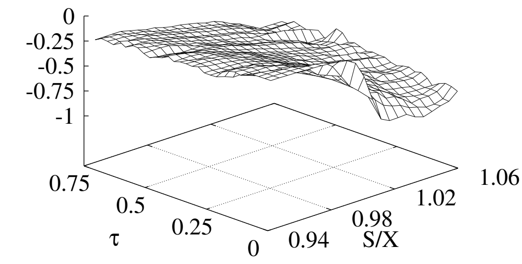
(a) BAW Delta $\frac{\partial C}{\partial S}$



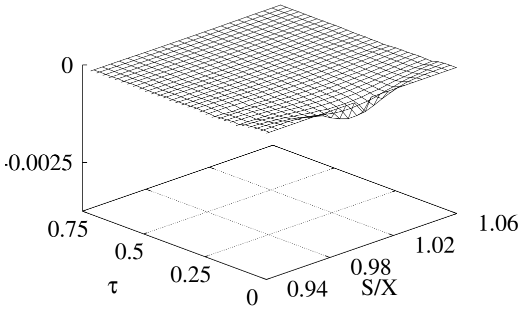
(b) Network Delta $\widehat{\frac{\partial C}{\partial S}}$



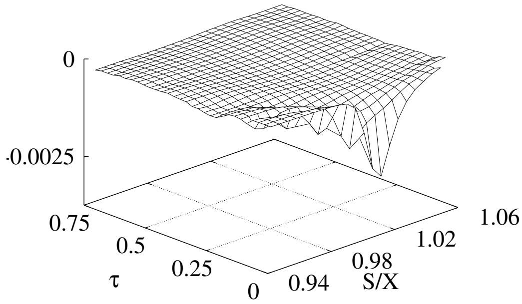
(c) BAW Dual Delta $\frac{\partial C}{\partial X}$



(d) Network Dual Delta $\widehat{\frac{\partial C}{\partial X}}$



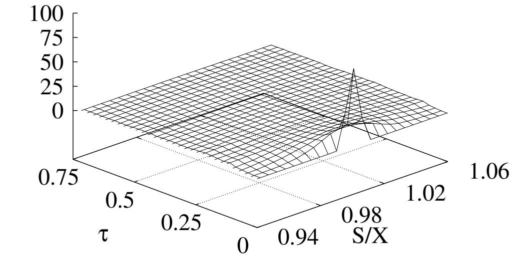
(e) BAW Theta $\frac{\partial C}{\partial \tau}$



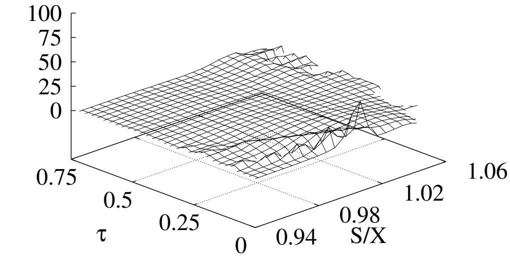
(f) Network Theta $\widehat{\frac{\partial C}{\partial \tau}}$

For higher-order derivatives we achieve less accurate approximation results for a given network topology - see figure A.6. Both Gamma and Speed exhibit inaccurate values in certain border areas, where data points are scarce. In case of Gamma we notice a violation of convergence criteria in these regions (values < 0).

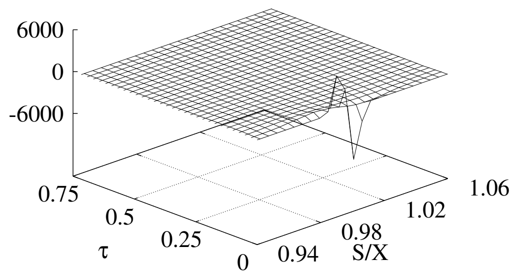
Figure A.6: Higher-order partial derivatives approximation



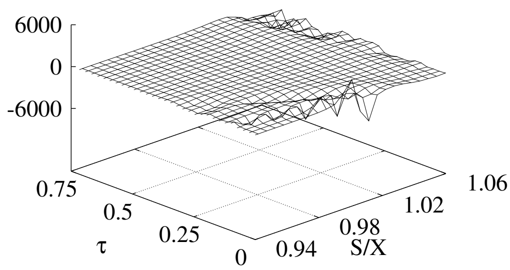
(a) BAW Gamma $\frac{\partial^2 C}{\partial S^2}$



(b) Network Gamma $\widehat{\frac{\partial^2 C}{\partial S^2}}$



(c) BAW Speed $\frac{\partial^3 C}{\partial S^3}$



(d) Network Speed $\widehat{\frac{\partial^3 C}{\partial S^3}}$

In order to evaluate the performance more precisely, we introduce in table A.2 a selection of accuracy metrics.

While ME and RMSE are not comparable between different Greeks, we add two normalized RMSE measures. Since Theta, Gamma and Speed deflect only to a small region around the ATM expiry, an approximation of the entire surface is particularly difficult. However, the NRMSE is relative low for this Greeks, because the majority of data points are zero.

Table A.2: Approximation accuracy

Function		Convergence	Error measure[a]				
			$\bar{R}^2$	ME	RMSE	NRMSE	CV
Price	C	> 0	0.9997	0.0000	0.0003	0.0039	0.0133
Delta	$\partial C/\partial S$	$[0, 1]$	0.9858	0.1266	0.1459	0.14591	0.2866
Dual Delta	$\partial C/\partial X$	$[-1, 0]$	0.9850	-0.1072	0.1251	0.1251	-0.2527
Theta	$\partial C/\partial \tau$	< 0	0.4192	0.0002	0.0003	0.1370	-2.1372
Gamma	$\partial^2 C/\partial S^2$	> 0[b]	0.6415	1.8163	4.0271	0.0484	0.6554
Speed	$\partial^3 C/\partial S^3$		0.0636	21.2067	640.5369	0.0417	-57.3113

[a] $\bar{R}^2$ denotes the adjusted R squared, ME denotes the mean error, MAE denotes the mean absolute error and RMSE denotes the root mean squared error. NRMSE denotes the normalized RMSE, where the RMSE is divided by the range of observed values. CV denotes the coefficient of variation of the RMSE, where the RMSE is normalized to the mean of the observed values.
[b] Occurrence of convergence violation.

4.4 *Discussion*

The results lead to the conclusion that one can possibly improve the approximation as follows: First, the network topology can be certainly improved, e.g. by the inclusion of further neurons. Secondly, the approximation can be divided into different regions in order to depict partial derivatives in exactly this area more closely.

Since the NN only trains on price functions without knowledge of their derivatives we have to suffer disadvantages for the NN. This is especially true for higher-order derivatives. For this reason, we might train directly on price sensitives as proposed in Carverhill and Cheuk (2003). However, as hedge-ratios predict price changes, they can be derived from option price movements. We would expect that the approximation to higher derivatives can be significantly improved. Nevertheless, the result highly depends on the accuracy of approximating price sensitives.

Finally, we give a critical appraisal for practical purposes. Of course, the learning network pricing method is highly data-intensive, requiring large quantities of historical prices to obtain a sufficiently well-trained network. Therefore, such an approach would be inappropriate for thinly traded options, or newly created options. Furthermore, network approximations involve weights as a kind of regression coefficients which need to be calibrated and recalibrated. A similar category of methods uses regression techniques to fit an analytical approximation based on a lower bound and an upper bound of an American option (Johnson (1983), and Broadie and Detemple (1996)). Another drawback is that these methods are not convergent. However, if an appropriate network is found, the derived network approximation, which is an analytical formula, will likely be very efficient computationally.

5 CONCLUSION

In the absence of any closed form formula for American options, a reliable analytical approximation is obviously highly desirable. Many efficient and accurate analytical methods for pricing American options exist. However, while these methods can produce option prices with sufficient accuracy, they often do give less accurate prices in particular market situations. In this paper, we propose a numerical approximation for American call option prices and its partial derivatives based on neural networks.

To evaluate its usability, we perform a trading simulation with artificially derived intra-day tick data of EUR/USD FX options. Our purpose here is to demonstrate that multilayer feedforward networks with only one single hidden layer and fairly arbitrary hidden layer activation functions are capable of arbitrarily accurate approximation to an option pricing function and its derivatives. With a given network topology we can derive a suitable approximation of option prices and its first-order partial derivatives, but the approximation accuracy decreases for higher-order derivatives. One useful solution might be to train directly on approximated Greeks.

From this point of investigation, further research steps are thinkable and we recommend to augment network topologies to achieve more robust results. This could be either regime-switching network architectures or separate training of desired Greeks. Nevertheless, we think that NNs could be a useful approximation tool beside other pricing models for particular market situations.

B
THE »PRICING AND HEDGING OPTIONS« PAPER

Real-time Pricing and Hedging of Options on Currency Futures with Artificial Neural Networks

Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2014). *Real-time Pricing and Hedging of Options on Currency Futures with Artificial Neural Networks*. Journal of Forecasting **33** (6), 419-432.

ABSTRACT

High-frequency trading and automated algorithm impose high requirements on computational methods. We provide a model-free option pricing approach with neural networks, which can be applied for real-time pricing and hedging of FX options. In contrast to well-known theoretical models, an essential advantage of our approach is the simultaneous pricing across different strike prices and parsimonious use of real-time input variables. To test its ability in purpose of high-frequency trading, we perform an empirical run-time trading simulation with a tick data set of EUR/USD options on currency futures of four weeks. In very short non-overlapping 15 minutes out-of-sample intervals theoretical option prices derived from the Black model compete against option prices through two different neural network topologies. We show that the approximated pricing function of learning networks is suitable for generating fast run-time option pricing evaluation as their performance is slightly better in comparison to theoretical prices. The derivation of the network function is also useful for performing hedging strategies. We conclude that the performance of closed-form pricing models depends highly on the volatility estimator, whereas neural networks can avoid this estimation problem but require market liquidity for training.

KEYWORDS

Option Pricing, Delta-hedging, Neural Networks, High-Frequency Data

DOI `10.1002/for.2311`

JEL C45, C52, C61, C63, G12

C
THE »FORECASTING RENMINBI QUOTES« PAPER

Forecasting Renminbi Quotes in the Revised Chinese FX Market - Can We get Implications for the Onshore/Offshore Spread-Behaviour?

Spreckelsen, C.v. , Kunze, F. , Windels, T. and Mettenheim, H.-J.v. (2014). *Forecasting Renminbi Quotes in the Revised Chinese FX Market - Can We get Implications for the Onshore/Offshore Spread-Behaviour?* International Journal of Economic Policy in Emerging Economies **7** (1), 66-76.

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ABSTRACT

Since 2011 China attempts to internationalize its currency by allowing more cross-border trade to be settled in Renminbi (RMB). Via the so-called RMB Trade Settlement Scheme trade partners are able to pay and to be paid in RMB offshore. Due to the mostly closed mainland (onshore) market, both markets - dealing with the same currency (RMB) - are separated, whereas CNY refers to the onshore and CNH refers to the offshore market. In this paper we provide a two-step investigation of the RMB markets. First, we investigate the short-term forecasting performance of spot CNY with GARCH-type and neural network models. Second, we attempt to uncover the benefits of relationships between onshore and offshore RMB. This is achieved by simulating both RMB time series in a multivariate way. Our conclusion is, that our proposed models lead to a better understanding of the still young volatility behaviour of the two different RMB series.

KEYWORDS

Renminbi (RMB) FX Markets, Spread Behaviour, Spot Price and Derivatives Forecasting, Neural Networks, GARCH

DOI `10.1504/IJEPEE.2014.059896`

JEL C45, C53, G14, G17, F31

Forecasting Renminbi Quotes in the Revised Chinese FX Market – Can We get Implications for the Onshore/Offshore Spread-Behaviour?

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1 INTRODUCTION

For decades gaining insights in the foreign exchange (FX) markets and improving the forecasting performance has been in the centre of attention of many academics as well as financial market professionals. According to Cooper (1984) and Basse (2006), we can observe this phenomena not until after the breakdown of the Bretton Woods system and the introduction of flexible exchange rates in many countries. On the one hand the performance of professional forecasters has always been subject to a lot of critique - for a critical discussion about forecasting FX see Chinn and Meese (1995). Recently, Cheong et al. (2012) showed that exchange rates follow a martingale process at short horizons, but over long horizons are less likely to follow a random process and may contain some predictable structure. Conversely, forecasting models do not perform better than simple naive forecasts.

One of the first steps in forecasting exchange rates is to identify the underlying exchange regime. In general, international financial markets as a whole do not follow at all a one size fits all approach. This is especially true for FX markets where the underlying regimes change over the course of time as well as from country to country. For example Frankel (1999) roughly classifies exchange rate regimes to be in the flexible corner, to be intermediate or in the fixed corner respectively. In this paper we will focus on one special case of an intermediate exchange regime which is to some extent similar to what for example Calvo and Reinhart (2002) characterized as soft peg. Although the case of China is not discussed in their paper, the authors' work leads us to the research topic of our analysis: The exchange markets for the Chinese markets.

The main goal of our work is to gain insights in the comparatively new market for offshore RMB (CNH spot market) and to detect first indications for feasible forecasting models for the onshore RMB (CNY spot market) respectively to improve CNY spot forecasts. We employ a simple GARCH model as well as neural networks. We do also analyze the somewhat older NDF market for RMB for which for example Ding et al. (2012) found a strong relationship with the CNY spot rate. As their work deals with the three RMB markets until June 2011 and since then the CNH market grew quite rapidly and seems to be replacing the NDF market, we lay our main focus on the CNH market.

The paper is organised as follows. Section 2 gives a short introduction about the Chinese FX market. Next, we introduce our methodology of neural networks and alternative statistical time series models. Section 4 describes the data and data preparation. Section 5 gives a brief introduction about our forecasting strategy. We evaluate our forecasting results and for further discussion. Finally, section 6 summarizes our conclusions and gives a brief outlook on further research.

2 RMB ONSHORE AND OFFSHORE FORWARD EXCHANGE MARKET

Although the rise of the Chinese currency is more present in the current debate of the future global currency structure than ever before the Chinese exchange rate regime still seems like a Gordian knot with respect to forecast performance. The reasons for the more and more intensifying discussion are not surprisingly manifold. On the one hand the economic weight of China in terms of nominal GDP and trade flows is pushing the debate in the direction of an international Chinese currency or even a displacement of the US-Dollar as the "No. 1" world currency. This is doubtless not to be seen in the foreseeable future. Much more realistic is the on-going discussion whether China's currency will reach the status of an international currency within the next five years or so; see for example Chen and Hu (2013). See for example Zhang (2013) for a good overview of the impacts related to an open Chinese capital account.

In the context of exchange rate regimes China currently uses a managed float with a target central parity where the central bank allows a movement up to $\pm 1.00\%$ in bilateral exchange rates within a given day (Tian and Chen (2013), although the authors still refer to the $\pm 0.50\%$ borders which have been double in April 2012). One large by-product of China's exchange rate regime which affords interventions of the People's Bank of China (PBOC) on a large scale is the accumulation of huge foreign exchange reserves. The huge amount of foreign exchange reserves did also fire the discussion on the substantial imbalances on the global financial markets. Not surprisingly, academic researchers, e.g. Liu and Pauwels (2012), also try to find evidence for a causal relationship between political pressure and appreciation of the RMB. As we are interested in forecasting for the Chinese FX markets this - without question very important - field of research will not be dealt with in the remainder of this paper.

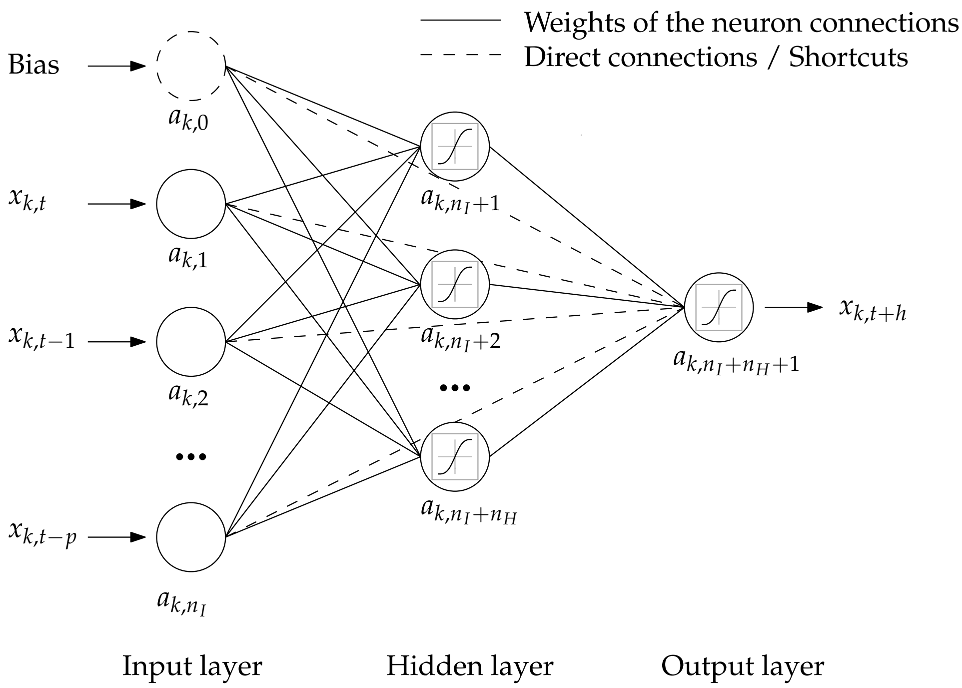
We will rather focus on one of the most unique features of the Chinese foreign exchange markets: the dual characteristic of the market. The uniqueness comes from the two separated markets for the RMB (or Chinese Yuan) namely the onshore (currency code CNY) and offshore (currency code CNH) market. The onshore Yuan stands for the inconvertibility of the Chinese currency under the capital account. Whalley and Chen (2013) discuss whether the CNH should be seen as a so-called stepping stone to full convertibility or as a workaround (internationalization without convertibility) and also give a very good overview of the two RMB markets. Under the expression RMB market one can subsume a substantial variety of financial market products whereas onshore products are traded in CNY and offshore products are traded in CNH, i.e. spot trading, forward products, interest rate and also cross currency products. Ding et al. (2012) point out the starting point of offshore trading has been marked by the PBOC in July 2010. Before that point in time the main focus of attention with subject to Chinese exchange rates has been on the market for non-deliverable forwards (NDF). Amongst others, Colavecchio and Funke (2008) analyzed the impact of volatility spill-overs from the Chinese NDF market on several Asia-Pacific markets using multivariate GARCH techniques. They found out that Chinese NDFs in fact had impacts on China's trading partners' currencies. But these impacts did vary to a large extend due to different financial integration.

Currently the focus of the financial industry and that of a growing of amount academic researchers is on China's offshore markets with Hong Kong being the most important and best developed. The Hong Kong market - often referred to as mainland China's test vehicle for free trade of the Chinese currency as well as bonds denominated in RMB (see for example Fung and Yau (2012)) - has also been highlighted in the People's Republic's most recent five-year plan. See for example Loechel et al. (2013) who examined the relationship between offshore and onshore government bond yields. According to Fung and Yau the state planners want the offshore market of the special administrative region to support the RMB in becoming an international currency. Having the same currency RMB being traded in three different "markets" - onshore, offshore and NDF - raises inevitably the questions of parity.

3 METHODOLOGY

For purpose of forecasting Neural networks (NN) can be described as non-linear input-output models. They provide the basis for an entirely different approach to the analysis of time series. A general introduction in neural network for market application is described in Priddy and Keller (2005), Wang (2005) and Li and Ma (2010). The connections between inputs and outputs are typically made via one or more hidden layers of neurons, sometimes alternatively called processing units or nodes. NN also appear to have potential application in time series modelling and forecasting. Nevertheless, the success of NN modelling depends on a suitable topology or architecture. This includes determining the number of layers, the number of neurons in each layer and which variables to choose as inputs and outputs. Figure C.1 shows an example of a neural network topology for time series forecasting purposes.

Figure C.1: Topology of a typical NN for time series forecasting



Example with one hidden layer and a various number of neurons. The output, e.g. the forecast variable, depends on the lagged input values at times $t, t-1, \ldots, t-p$.

Inputs and outputs $(x_{k,t-l}, x_{k,t+h})$ represent a training pattern k. The number of hidden layers is often taken to be one, while the number of hidden neurons is found heuristically. In the case of time series prediction, feedforward NN use the past lagged observations $l = 0, 1, \ldots, p$ as inputs to conduct h-step ahead forecasts. They do not require any assumptions relating to the underlying data-generating process.

More formally, a h-step ahead forecast of exchange rates $\hat{x}_{k,t+h}$ is computed using lagged input variables $(x_{k,t}, x_{k,t-1}, \ldots, x_{k,t-p})$ as follows:

$$\hat{x}_{k,t+h} = f(x_{k,t}, x_{k,t-1}, \ldots, x_{k,t-p}), \tag{C.1}$$

where $f(\cdot)$ denotes the function determined by the network. One of the input variables will usually be a constant (bias). The NN attempts to find the best possible approximation of the function $f(\cdot)$ as a complex combination of elementary non-linear functions. This approximation is coded in the neurons of the network using weights that are connected with each neuron. These weights effectively measure the 'strength' of the different connections and are parameters that need to be estimated from the given data.

We further assume there are H neurons in one hidden layer and then attach the weight w_{ij} to the connection between the ith input neuron and the jth neuron in the hidden level. Given values for the weights, the value to be attached to each neuron may then be found in two stages. First, a linear function of the inputs is found:

$$a_j = w_o + \sum_{l}^{p} w_{ij} \hat{x}_{t-l}. \tag{C.2}$$

For $j = 1, 2, \ldots, H$. Second, the quantity a_j is converted to the final value for the jth neuron by applying an activation function - in our case we use the hyperbolic tangent, $\tanh(a_j)$. Having calculated values for each neuron, a similar pair of operations can then be used to get the predicted value for the output using the values at the H neurons. This requires a further set of weights w_j to be attached to the links between the neurons and the output. Overall the output $\hat{x}_{t+h}$, is related to the inputs by the following expression:

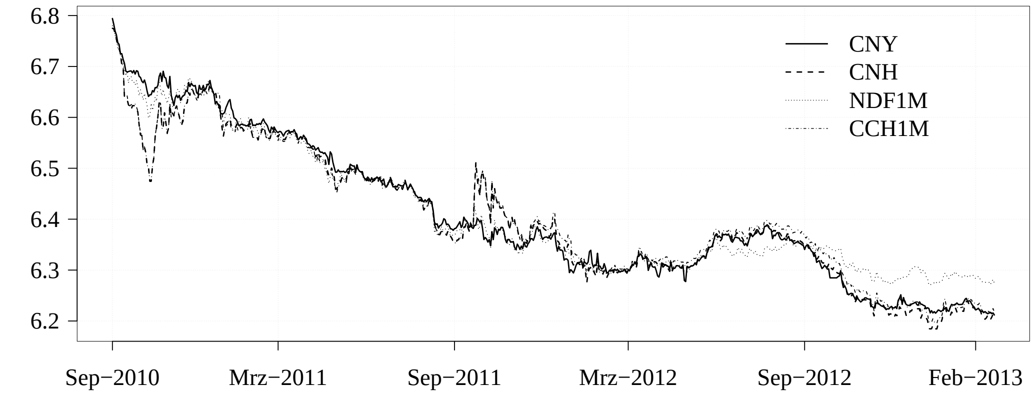
$$\hat{x}_{k,t+h} = a_o \left[\left(\sum_j w_j \tanh \left(\sum_l^p w_{ij} \hat{x}_{k,t-l} \right) + w_o \right) \right], \tag{C.3}$$

where a_o denotes the activation functions at the output layer. It is also easy to incorporate further input variables into NN model. In this case, we are able to extend such an univariate NN to a multivariate topology. In addition to the NN model, we apply a GARCH(1,1) model with a simple AR(1) term.

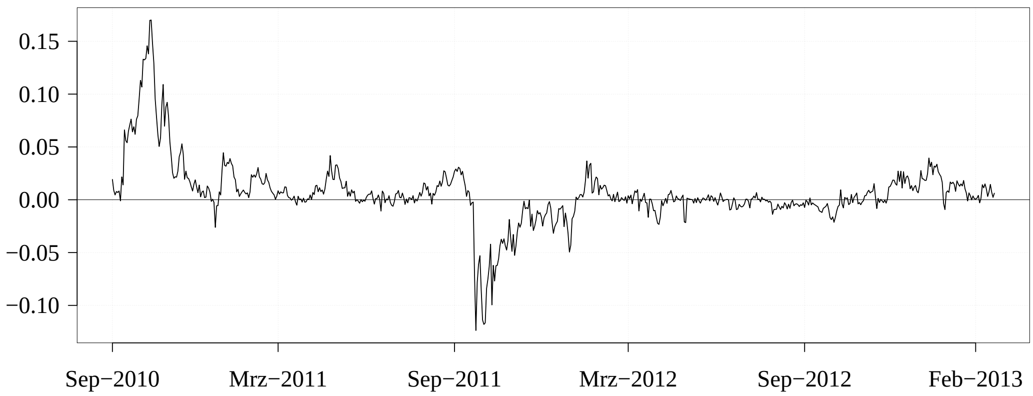
4 DESCRIPTION OF DATA

We collect daily exchange rate data for onshore spot (CNY), offshore spot (CNH), one-month offshore NDF and CNH forward rates from Bloomberg. Although some studies argue in favour of longer NDF maturities, we use one-month rates given one-month NDFs are less prone to purely speculative pressures, more liquid, and less susceptible to exaggerated price swings. Our sample period spans 08 September 2010 to 20 March 2013. Figure C.2a shows data points of the mentioned series.

Figure C.2: Renminbi quotes in the sample period from 08 September 2010 to 20 March 2013



(a) Spot and forward Rates



(b) Spread between the onshore and offshore price

As one can easily see in figure C.2b there exists a significant spread between the onshore and offshore price of the Chinese currency. Yu (2012); Rhee and Sumulong (2013) refer to the CNH-CNY-spread as a potential source of arbitrage. Following the author corporates on mainland China may have substantial opportunities for arbitrage especially in times of high CNH-CNY-spreads. As figure C.2b further shows there in fact are times when the CNH is significantly stronger against the US-Dollar than the CNY. This seems to be especially true when market participants expect a fastening appreciation of the Chinese currency. One reason for a widening CNH-CNY spread is the fact that arbitrage opportunities are subject to major constraints.

Summary statistics of daily spot and forward prices are presented in table C.1 for the whole period.

Table C.1: Descriptive statistics for the onshore/offshore spot and forward prices[a]

	Spot			Forwards	
	Spread	CNH	CNY	NDF1M	CNH1M
N[b]	661	661	661	661	661
Mean	0.01	6.40	6.41	6.41	6.41
SD	0.03	0.13	0.14	0.13	0.13
Skew	1.08	0.42	0.62	0.89	0.44
Kurtosis	11.43	2.27	2.27	2.49	2.37
Jarque-Bera[c]	2085.29***	33.87***	57.27***	93.59***	32.46***
Ljung-Box[d]	4802.62***	7056.07***	7326.49***	7249.67***	7005.21***
ARCH[e]	562.06***	644.61***	647.27***	646.31***	644.14***
ADF[f]	−3.69**	−2.81	−1.68	−1.54	−2.81
ADF (differences)	−7.72***	−7.29***	−8.19***	−8.37***	−7.35***

[a] Data are daily in the period 08 September 2010 to 20 March 2013. $*$, $**$ and $***$ denote the significance level at 10, 5 and 1%.
[b] N shows the number of daily observations. Skewness and kurtosis are estimated centralized third and fourth moments of the data.
[c] The Jarque-Bera test for normality is distributed as $\chi^2(2)$.
[d] $Q(12)$ is the Ljung and Box Q statistics on the first 12 lags of the sample autocorrelation function.
[e] ARCH(12) is the test for the 12th-order autoregressive conditional heteroscedasticity.
[f] ADF is the Augmented Dickey and Fuller test on the first 12 lags. The ADF regressions include an intercept term.

The result's excess kurtosis in the CNY, and the skewness does not necessarily imply a symmetric distribution. The Jarque-Bera tests indicate departures from normality for both spot and forward prices. This seems to be more acute for the CNY. The Ljung-Box $Q(12)$ statistic on the first 12 lags of the sample autocorrelation function and Engle's ARCH test indicate significant serial correlation and existence of heteroscedasticity, respectively. Augmented Dickey Fuller (ADF) unit root tests indicate that all variables are first-difference stationary, but the levels indicate, that price series follow unit root processes.

5 FORECASTING RESULTS

For purpose of forecasting, we conduct a rolling-window technique of 100 data points to generate one step-ahead forecasts. The first insample runs from 08 September 2010 to 25 January 2011. The insample subset is used to estimate the statistical models and identify the neural network structure while the second is used for independent out-of-sample prediction comparison. As recommended in Tashman (2000), in order to avoid the bias induced by serially correlated overlapping forecast errors, we recursively augment our estimation period by h-periods ahead every time. This implies that we get a sample of 560 daily observations for the one step-ahead forecasting period. All models seem to be well specified, as indicated by relevant diagnostic tests.

The forecast performance of each model is assessed using the conventional root mean square error metric (RMSE) and Theil's U statistic. The latter allows a relative comparison of formal forecasting methods with a naïve model, a no-change random walk (RW). Statistical performance measures are often inappropriate for financial applications. Trading strategies guided by forecasts on the direction of price change may be more effective and generate higher profits. Therefore, predicting the direction (Directional in %) is a practical issue which usually affects a financial trader's decision to buy or sell a contract. The trading simulation assumes that, at the beginning of each trading day, the investor will invest 1 monetary unit at the beginning of each contract period. Consider an exchange rate whose prices fluctuate from day to day and the mid price on the tth day is x_t. We can generate trading signals now by the following rule:

$$\begin{cases} \text{long, if} & \hat{x}_{t+1} > x_t \\ \text{short, if} & \hat{x}_{t+1} < x_t \end{cases}$$

A long signal is to buy contracts at the current price, while a short signal is to sell contracts at the current price. So far, we can compute a net gain at the end of our out-of-sample period.

The forecasting performance of each model is presented in matrix form in table C.2 for all currencies. We separate all results in univariate and multivariate classes: the univariate models consist of single series of CNY, CNH and their spread. We exclusively analyze the CNY in a multivariate way by incorporation of the one-month forward rates NDF and CNH respectively.

Some regularities stand out from the table.

Onshore Spot and Offshore Spot Rates

We first examine the relationship between onshore and offshore spot rates. We find that the correlation between CNY and CNH returns during the entire sample is statistically and economically significant (0.9789). It is remarkable that predicting the spread is more difficult than the offshore CNH or onshore CNY. For the spread-behaviour we conclude that both markets still have a moderate level of comovement. Thus, there might exists a low level of information integration between CNY and CNH rates.

Onshore Spot and Offshore Forward Rates

We now shift our focus to both contemporaneous and lead-lag relationships between onshore Yuan spot rates and offshore NDF or CNH rates. However, onshore spot exchange rates of RMB are not only influenced by spot foreign market, but also offshore forward market. When examining onshore spot trading against offshore

Table C.2: One step-ahead forecasting performance for spread, CNH and CNY[a]

		Univariate			Multivariate CNY	
Model	Measure	Spread	CNH	CNY	NDF1M	CNH1M
RW[b]	$\bar{R}^2$	0.8276	0.9912	0.9957	–.–	–.–
	RMSE	0.0088	0.0099	0.0069	–.–	–.–
	Theil's U	1.0000	1.0000	1.0000	–.–	–.–
	Directional %	–.–	–.–	–.–	–.–	–.–
	Net Gain	0.0000	0.0000	0.0000	–.–	–.–
AR(1)-GARCH[c]	$\bar{R}^2$	0.8275	0.9910	0.9956	–.–	–.–
	RMSE	0.0087	0.0101	0.0069	–.–	–.–
	Theil's U	0.9876	1.0178	0.9983	–.–	–.–
	Directional %	0.6219	0.5161	0.5326	–.–	–.–
	Net Gain	0.0838	−0.0338	0.0264	–.–	–.–
NN	$\bar{R}^2$	0.8265	0.9876	0.9951	0.9945	0.9954
	RMSE	0.0089	0.0118	0.0073	0.0077	0.0071
	Theil's U	1.0153	1.1952	1.0636	1.1216	1.0288
	Directional %	0.5108	0.5425	0.5254	0.4366	0.5072
	Net Gain	0.0770	0.0275	0.0848	−0.1332	0.0761

[a] The table shows forecasting performance measures in the period 26 January 2011 to 20 March 2013.
[b] RW means a no-change random walk. Hence, the directional performance is not calculable and the net gain is zero.
[c] GARCH means the GARCH(1,1) model with an AR(1) term.

NDF trading, our results show no ambiguous picture that onshore spot rates are influenced by offshore forward rates. This is not in line with prior results, where the CNY and NDF markets became even more informatively integrated after the CNH began trading. Specifically, while the NDF is a contract whose forward curve acts like a futures curve on onshore Yuan spot rates, the CNH is a spot rate whose forward curve acts more like an onshore interest rate curve. Thus, NDF rates more closely track onshore Yuan spot rates whereas CNH rates more closely track onshore interest rates. We think, that further research at this point is necessary. Further, the introduction of offshore spot trading is associated with an increase in both cross-market comovement (higher returns correlations) and information contribution.

Although one might argue that further integration of the CNY and the CNH market could help to improve FX forecasts for the revised Chinese FX market our results do not support our assumption of a parity between the CNY and CNH. On the one hand the fact that the used forecasting methods do not outperform the naive RW forecasts points to the direction that the price movements in the Chinese FX markets are similar to the movements in developed economies' FX markets, which are said to be rather efficient. On the other hand we found strong evidence that structural breaks do exist in the RMB markets. The existence of a significant as well as non-stationary CNH-CNY-spread thus points to FX market far from being arbitrage free. Hence, CNH and CNY spot rates do not seem to tend towards parity. Having in mind that the CNH market is rather new and subject to a lot of regulatory changes within a short time frame this is not surprising at all. The paradox lies in the fact that from a forecasting perspective Chinese FX market seem to be rather effective although substantial capital controls do exist.

In summary, the behaviour of the CNH-CNY-spread might give us an indication why CNY forecasts seem to be subject to inaccuracy. As the CNH market is rather new and not as liquid as much more mature FX markets structural breaks respectively regime shifts can not be ruled out. Due to this conclusion, we perform a simple regression of CNY and CNH and the Quandt-Andrews test for structural breaks. As we analyze daily spot rates we utilize the heteroscedasticity and auto-correlation consistent HAC (Newey-West) approach. We found a very strong indication for at least one breakpoint within the given time frame, i.e. January, 20th, 2012. For further research as well as to improve forecast accuracy structural breaks respectively regime shifts within the CNH-CNY-spread should be analyzed further.

6 CONCLUSIONS AND RECOMMENDATIONS

In this paper, we have examined the influence of the offshore CNH trading on onshore RMB rates (CNY). In contrast to prior studies we assume that the new CNH trading market becomes more relevant for the onshore CNY. Thus, we expect a tendency for parity between these two rates. To proof our assumption we predict single CNH and CNY rates, as well as multivariate effects of forward rates on the CNY with a GARCH-type and a neural network model. In summary, our results give us no ambiguous evidence to confirm our assumption. Having in mind that the CNH market is rather new and subject to a lot of regulatory changes within a short time frame this is not surprising at all. The paradox lies in the fact that from a forecasting perspective Chinese FX market seem to be rather effective although substantial capital controls do exist.

Nevertheless, several extensions for further research are necessary. From our point of view further research should focus on structural breaks and much more advanced forecasting methods. First, we would incorporate statistical multivariate GARCH models to analyze the relationship between the CNH market and CNY rates in detail. We would expect to get practical hints for a better specification of our neural network model to improve forecast accuracy. In addition, we recommend investigations of structural breaks respectively regime shifts within the CNH-CNY-spread. It should be noted that our analysis is only concerned with the initial impact of RMB offshore spot trading. Results may be temporary effects brought about by policy changes or policy change uncertainty.

D

THE »FINANCIAL DECISION SUPPORT SYSTEM« PAPER

Steps towards a High-frequency Financial Decision Support System to Pricing Options on Currency Futures with Neural Networks

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ABSTRACT

In this paper we present steps towards a model-driven Financial Decision Support System (FDSS) to pricing options on currency futures, which can be embedded in a high-frequency trading process. Due to the difficulty of option valuation, we provide an alternative heuristic option pricing approach with neural networks. We show that the use of neural networks is not only suitable in generating accurate trading signals, but also in generating automated fast run-time trading signals for the decision taker. To achieve this, we conduct an experiment with an empirical tick data set of EUR/USD options on currency futures of four weeks. An essential advantage of our approach is the simultaneous pricing across different strike prices and parsimonious use of input variables. Nevertheless, we also have to take particular limitations into account, which give us useful hints for further research and steps.

KEYWORDS

Financial Decision Support System, Neural Networks, High-frequency Data, Trading Systems, Option Pricing, Design Science

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JEL C14, C45, C63, G11, G21

Steps towards a High-frequency Financial Decision Support System to Pricing Options on Currency Futures with Neural Networks

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1 Motivation and Research Formulation

Since the introduction of electronic brokers in the foreign exchange (FX) interbank market in 1992, the FX market is a vast subject. Advances in computer technology and automated algorithm trading have supercharged the transmission and execution of orders, making use of the big data - and established a new phenomenon: "High-frequency trading". Today, efficient trading systems are taking a more important position in the financial FX market's structure. Decision Support Systems provide management support system technologies for better decision-making. This leads to three major challenges:

1. Financial trading systems need support in making correct trading decisions, which are rather complex but important for participants in financial markets (decision problem).
2. An accurate market valuation of option products in the FX market is still difficult and needs appropriate models and techniques (option pricing problem).
3. From the operational perspective, the high speed of computer-driven decisions requires a particular comfort level with computer-driven execution (performance problem).

In this paper we face these challenges by developing steps towards a Financial Decision Support System (FDSS) based on artificial neural networks (NN) to pricing options on currency futures. We are motivated by our following research question:

> *"How can a model-driven FDSS help to approximate options' market prices, and determine accurate and efficient trading decisions in a high-frequency process?"*

Considering the evolution of non-linear dynamic systems to improve decisions is certainly not a new idea. There is a wide range of research in context of model-driven Decision Support systems, e.g. Gupta (2006), Weber (2008), Turban et al. (2010), Grosan and Abraham (2011) and Schuff et al. (2011). Financial services providers use information systems, in particular model-driven FDSS, for decisions under uncertainty - in our case to determine the value of options. Today, many FDSS use interactive and artificial intelligence computer-based systems like NN for decision making. Artificial intelligence programs like NN often learn from a priori given processes, data, etc. and corresponding appropriate decisions.

Second, accurate pricing of options is very important for decisions on risks and hedging. Option pricing is based on theoretical models developed by Black and Scholes (1973), Merton (1973) and Cox et al. (1979) with several extensions. Unfortunately these models are based on severally unrealistic assumptions. Bakshi et al. (1997), Laidi (2009) and Turban et al. (2010) emphasized that some models primarily address perceived weaknesses that are in use by financial decision makers. Permanently an unsatisfactory and quite artificial adaption to the true market conditions is necessary. In contrast to the theoretical pricing models NN algorithms as an alternative heuristic approach are applied to the option pricing and adopted to simulate the nonlinear behaviour of such financial derivatives. A general introduction in neural network for market application are described in Priddy and Keller (2005), Wang (2005) and Li and Ma (2010). First attempts of market price synthesis with NN were made in the 1990ies by Malliaris and Salchenberger (1993) and Hutchinson et al. (1994). Subsequent studies investigated particular option pricing approximations with NN (Garcia and Gençay (2000), Andreou et al. (2002, 2006), Amilon (2003), Bennell and Sutcliffe (2004) and Kohler et al. (2006)). Huang et al. (2010) present an alternative FDSS approach with non-parametric kernel regression for option trading. Many of these studies maintain the view that NN models are capable of generating better results in comparison to closed-form models like the Black Scholes formula in pricing options.

A new trading methodology, called high-frequency trading, is the third challenge for FDSS in context of trading options. According to Aldridge (2010), high-frequency is defined as quantitative analysis embedded in computer systems processing data and making trading decisions at high speeds and keeping no positions overnight. The advances in computer technology over the past decades have enabled fully automated high-frequency trading. Efficient high-frequency trading systems make a full range of decisions, from identification of underpriced or overpriced options, through optimal portfolio allocation, to best execution. A signal must be precise enough to trigger trades in a fraction of a second.

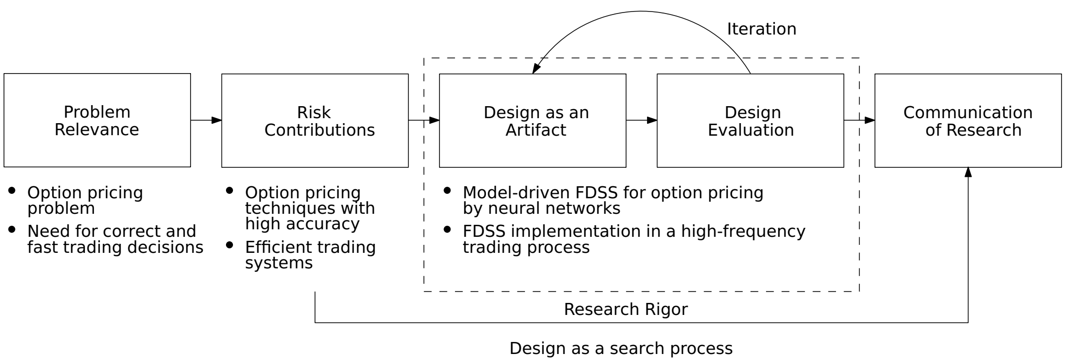
In this paper, we perform an empirical study of market price synthesis of options on FX futures contracts. The NN technology as a kind of core engine in the model-driven FDSS allows option sellers and buyers to approximate call option prices across different strike prices simultaneously. We focus on designing a high-frequency FDSS and the approximation ability of NNs. The proposed FDSS is also useful for out-of-sample pricing, hedging or currency forecasts. This leads to kind of currency forecasting technique. Especially currency forecasts have become extremely important for financial markets not until after the breakdown of the Bretton Woods system and the introduction of flexible exchange rates in many countries. For a discussion of the historical events in the late 1960s and early 1970s see, for example, Cooper (1984) and Basse (2006). For a critical discussion about forecasting FX see Chinn and Meese (1995).

We organize this paper as follows: First, we introduce our methodology for developing a model-driven FDSS with support of the design science paradigm. Next, we propose our high-frequency FDSS architecture for pricing and trading currency options. We outline NN methods as a core engine of FDSS and explain our network topology in case of option pricing. In section 4 we conduct an experiment with empirical tick data of EUR/USD options on currency futures. We analyze and evaluate our model results. In addition, we outline limitations of our work. The paper finishes with a brief conclusion and an outlook for further research.

2 METHODOLOGY

In this paper, we use the concept of design science of Hevner et al. (2004) and Hevner (2007) as a framework for developing a FDSS. Design science, as conceptualized by Simon (1996), supports a pragmatic research paradigm that combines a focus on the IT artifact with a high priority on relevance in the application domain. Thus, the objective of design science is to develop technology-based solutions to important and relevant business problems using methods and tools available to the researcher. Figure D.1 shows how we use the concept of design science for our research question.

Figure D.1: Our FDSS development methodology framework with design science research according to Hevner et al. (2004)



First, Problem Relevance deals with the importance of the problem. The difficulty in accurately estimating the price of an option has been described in a number of different publications. But correct and fast trading decisions are a fundamental task of trading systems. All classic theoretical models for option valuation have several constraints regarding accuracy, due to severally unrealistic assumptions - e.g. future volatility of the underlying price is assumed to be accurately estimable and is a priori known to seller and buyer of an option. Most enhanced approaches focus on specific advancements, but those perfectly specified option pricing models are therefore bound to be too complex and computationally intensive for high-frequency applications. Research Contributions shows that the work makes a specific contribution to information systems research, and this contribution needs to be verifiable. The contribution of this paper focuses on pricing options in a high-frequency trading process. It is highly significant, because financial institutions have a high stake in this business.

The central design cycle iterates between the core activities of building and evaluating the design artifacts and processes of the research. Design as an Artifact indicates that research has to develop a model, a method, or any other kind of construct. This paper can be described as part of FDSS research; therefore, the results should be used to develop a FDSS artifact that enables the pricing of currency options, finds the optimal trading time in the near future and leads to a run-time trading decision. FDSS provide information in the specific problem domain of finance using analytical decision models and techniques, in order to support an investor in making decisions effectively.

Today, model-driven FDSS use algebraic, decision analytic, financial, simulation, and optimization models to provide decision support. Option pricing is a nonlinear estimation problem that can be solved by several iterative methods. Hence, we focus on powerful NN approaches as a core engine in a model-driven high-frequency FDSS. NN are inspired by the way biological neural system works, such as the brain process information. In a nutshell, the information processing system is composed of a large number of highly interconnected processing elements (neurons) working together to solve specific problems. The most essential property of NN models is its ability of learning from sample sets. A well-trained NN is a mathematical function or algorithm which approximates the output of the patterns - in our case currency option prices - sufficiently accurately. In practical use, NNs give many advantages to the decision makers. They do not require any modeling or programming for matching inputs to outputs. Moreover, they are able to be run with missing or larger data. In consideration of these kinds of advantages, NN are used in a wide range of applications in engineering and management practices.

Design Evaluation indicates that the model must be evaluated. This especially applies to neural networks, because they have to be benchmarked against the real world and other widely used models. After evaluating the results, feedback can be used to refine the previous approach. The Rigor Cycle provides past knowledge to the research artifact to ensure its innovation. It describes how the methods of research need to be applied for the artifact to be successful. This further emphasizes the need to evaluate one's results. The question "how is the research artifact introduced into the application environment" is investigated through a Design as a Search Process. It means that the resulting model or artifact cannot be clear from the start of the process. Information systems need to be redesigned as they are developed. This also applies to the development of any other model. The last guideline, Communication of Research, presents results of information system research to the general public, specifically to audiences from business management and technology perspectives.

The seven design science guidelines assist in the research process. Information systems research focuses on creating an artifact, construct, model or any kind of methodology for the development of an information system. This applies to our work, because we present steps towards developing a high-frequency FDSS to pricing options on currency futures.

3 IMPLEMENTATION OF A HIGH-FREQUENCY FDSS TO PRICING OPTIONS ON CURRENCY FUTURES

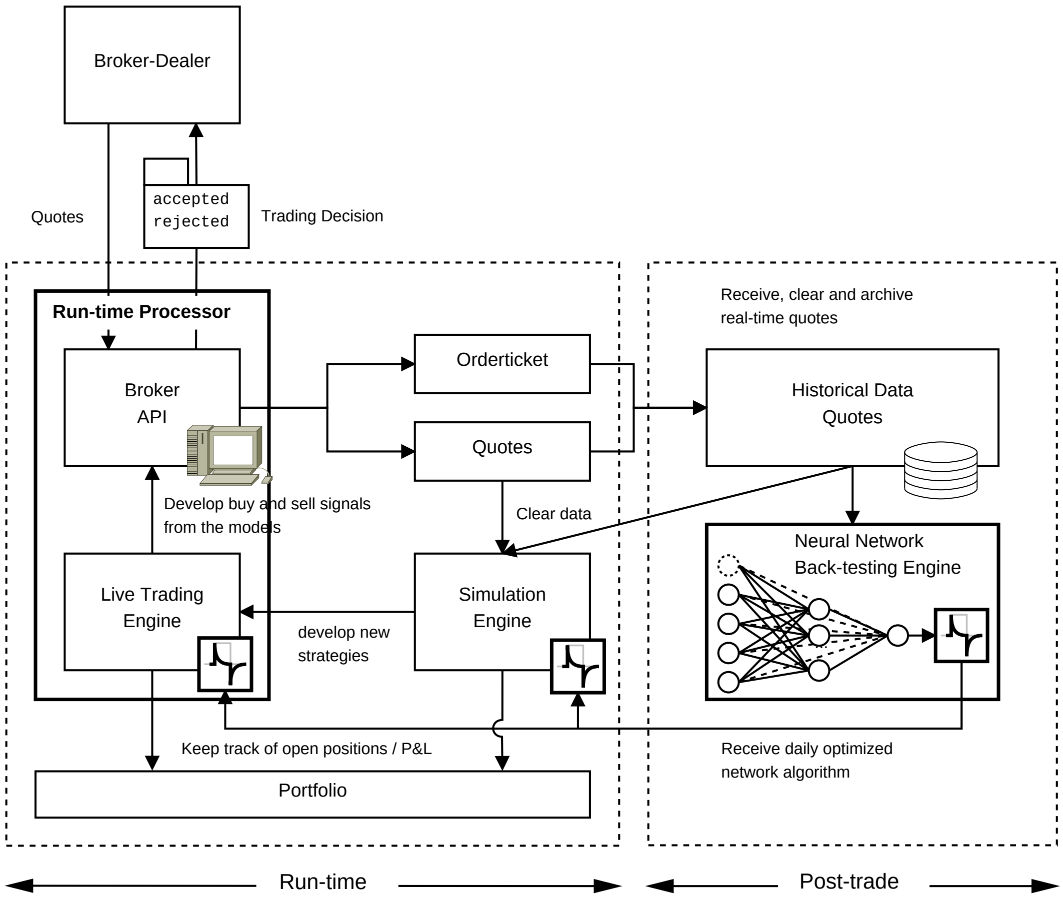
3.1 *Proposed FDSS Architecture*

Today, most high-frequency trading systems are built as algorithmic trading systems that use complex computer algorithms to analyze quote data, making decisions, and optimize trade execution. High-frequency trading systems require rapid hesitation-free decision making and execution. We concentrate only on generation high-frequency trading signals. The development of a fully automated trading system follows a path similar to that of the standard software development process and is not discussed in this paper. With help of the design science toolkit we are prepared to design steps towards a model-driven FDSS to pricing and trading currency options - embedded in a high-frequency process. Our resulting FDSS architecture is shown in figure D.2.

A successful high-frequency trading system adapts itself easily to contemporary market conditions. As a result, most high-frequency systems accept, process, and achieve volumes of quotes and other market data delivered at real-time frequency. The run-time processor is a computer program that performs the following three functions: Receive, evaluate, and achieve incoming quotes, uses the quotes as inputs to the live trading engine and outputs trading signals. In our case, the run-time processor receives the network algorithm from the NN back-testing engine before market opening. We explain the delivered algorithm in the next subsection in detail. Furthermore, run-time processors calculate run-time portfolio P&L. In summary, run-time processors contain the core logic of the trading mechanism, can be easily implemented and have the advantage of computing time saving.

The back-testing engine is typically based on the historical analysis identified to generate consistent positive returns over a significant period of time during the simulation and back-testing process. To ensure statistically significant inferences, the model training period T should be sufficiently large. In the live trading engine, a different quote module receives real-time tick data originating at the broker-dealers. An efficient high-frequency trading system does not stop there. The simulation

Figure D.2: Overview about the proposed FDSS to pricing and trading FX options - embedded in a high-frequency trading process



engine is an independent module that tests new trading strategies on past and run-time data without actually executing the trades. Once the back test performs satisfactorily, the system is switched to run on real-time data, the same data that feeds into the production system.

3.2 *Neural Network Topology*

The NN as a back-testing engine is the core engine of the FDSS. In case of pricing options on currency futures we have to calibrate the NN topology or architecture and choose appropriate variables. According to Black (1976), the theoretical fair call option price C_t^{BL} (Black 76 model) depends on the underlying futures price F_t, the strike price X, the time to expiration M (Maturity), the risk-free interest rate r up to expiration and the future volatility σ_F of the underlying price. The Black formula is similar to the Black-Scholes formula except that the spot price of the underlying is replaced by a futures price F_t. The only component that cannot be observed directly is the volatility of the underlying asset.

Neural networks face these problem by relaxing the unobservable volatility σ_F and r. Like the theoretical option price C_t^{BL}, the heuristic option price C_t^{NN} depends on the permanently available moneyness (F_t/X), which is the quotient of the underlying price F_t and the option's strike price X, the strike price X itself and the time to expiration M_t. Instead of r and the artificially estimated σ_F, we use the permanently available trading day t as direct input for the heuristic pricing model.

But how does the NN work? The basic process units of NN architecture are neurons which are internally in connection with neurons from subsequent layers. The ability of NNs to process depends on these connections which are named as weights. The weights give the abilities of prediction or classification to the system. Inputs and outputs (x_k, y_k) represent a training pattern k. Firstly, the inputs (x_k) are weighted and summed up. Then they are entered to an activation function $f(\cdot)$ - in our case the hyperbolic tangent transfer function tanh - in order to get an output (y_k) from the last neuron in the output layer. The weights are iteratively changed until the best loads are obtained. To find the right weights within a so-called training process thousands of multi-layer perceptrons with various topologies and with different weight initializations are trained.

We follow the argumentation of Anders et al. (1998) and Hornik et al. (1990), that feedforward networks with only one hidden layer and a output unit are able to approximate simultaneously its unknown derivatives up to an arbitrary degree of accuracy. The first layer includes the four major influencing variables $(F_t/X), X, M_t$ and t of a call option price. The second layer has a varying number of hidden neurons. The third layer contains only the trained options' market price. More formally, our 3-layered perceptron with shortcut connections has an auxiliary neuron N_0 (bias neuron) with $x_{k,0} \equiv \frac{1}{2}$, where $k = 1, 2, \ldots, n_p$ and n_p denotes the number of training and validation patterns. We have $N_1, \ldots, N_{n_e}$ input neurons, with $N_{n_e+1}, \ldots, N_{n_e+n_h}$ hidden neurons, where n_h is the number of hidden neurons and $n_h \geq 1$, with $N_{n_e+n_h+1} \ldots, N_{n_e+n_h+n_o}$ output neurons. Thus, our enabled 3-layered perceptron is defined by

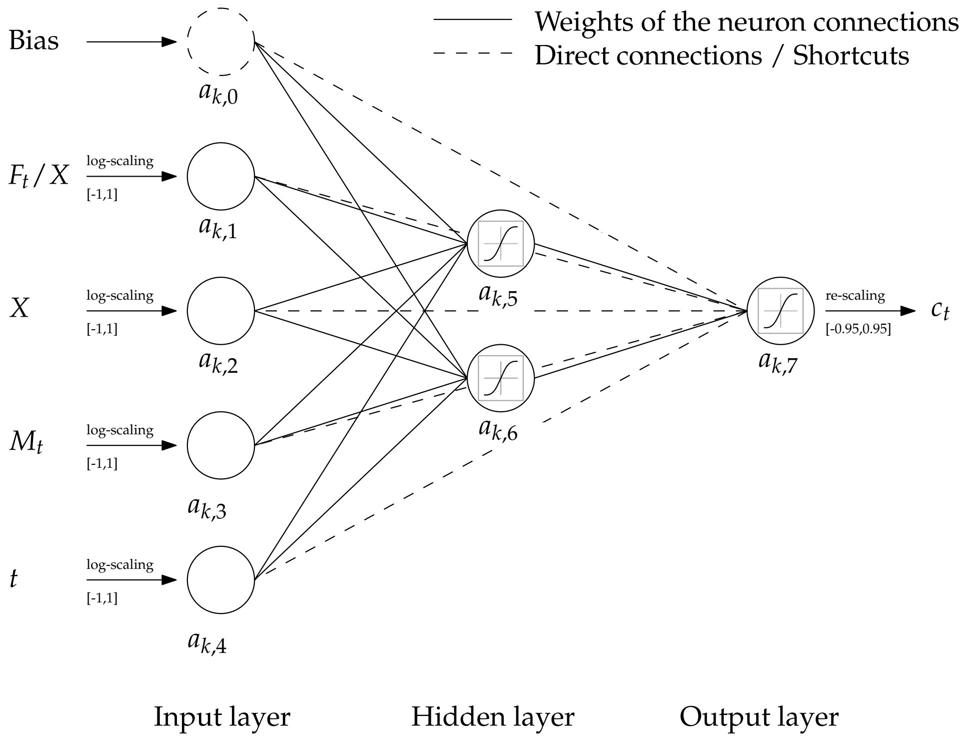
$$a_{k,i} := x_{k,i} \qquad \text{for} \quad i = 0, 1, \ldots, n_e, \tag{D.1}$$

$$a_{k,i} := \tanh\left(\sum_{j=0}^{n_e} w_{j,i} a_{k,j}\right) \qquad \text{for} \quad i = n_e + 1, \ldots, n_e + n_h, \tag{D.2}$$

$$a_{k,i} := \tanh\left(\sum_{j=0}^{n_e+n_h} w_{j,i} a_{k,j}\right) \quad \text{for} \quad i = n_e + n_h + 1, \ldots, n_e + n_h + n_o. \tag{D.3}$$

N_i's output for pattern (x_k, y_k) is denoted by $a_{k,i}$ and equations (D.1)-(D.3) yield the output of a feedforward network. According to Breitner (2000), we transform all output market prices C_t in option market premiums $c_t = (X + C_t - F_t)/F_t$, which can be easily re-computed to option prices. Figure D.3 shows the proposed NN topology.

Figure D.3: Our proposed neural network's topology (three-layered perceptron) used for market price synthesis



Combining the layers, the output - a heuristic option premium c_t^{NN} - can be written as a function $f(x;\theta)$, where θ stands for a vector of parameters and the function f determines how x and θ interact

$$f(x;\theta) = \tanh \underbrace{\left[\sum_{j=0}^{6} w_{j,i} \cdot \tanh \overbrace{\left(\sum_{j=0}^{4} w_{j,i} x_{k,i} \right)}^{\text{summing over input nodes}} \right]}_{\text{summing over hidden and input nodes}}. \tag{D.4}$$

To avoid over-fitting we employ the cross-validation technique. The idea of cross validation is to split the training set into two sets: a set of examples to train with I_t, and a validation set I_v. Out-of-sample pricing on the validation set is used to determine which model should be use, in which the error of the validation set is a minimum. Training a neural network amounts to choosing its biases and weights w_{ij} in order to minimize a accuracy criterion, e.g. the least squares of the observable output. The approximation quality of the NN can be estimated by means of the training and validation error functions

$$\varepsilon_t := \frac{1}{2} \sum_{k \in I_t} \Big(a_{k,7} W - y_k \Big)^2 \quad \text{and}$$

$$\varepsilon_v := \frac{1}{2} \sum_{k \in I_v} \Big(a_{k,7} W - y_k \Big)^2 .$$

Both training and validation error are exclusively affected by the used topology, i.e. number of inner neurons and shortcuts activation.

We perform our network training with the Fast Approximation with Universal Neural Networks (FAUN) neurosimulator. The FAUN neurosimulator uses fine-grained parallelization which allows easily achieved speedups on dual and quad core CPUs. FAUN also features coarse-grained parallelization using an easy to install grid computing client. It is possible to use clusters of heterogeneous workstations. Furthermore, using reverse accumulation and matrix algorithms allow a very efficient computation. This technical specifications make FAUN suitable for HFT, where computational requirements should be high and require special high performance computers.

4 EXPERIMENTAL DESIGN: PRICING OF OPTIONS ON CURRENCY FUTURES

4.1 *Description and Preparation of Tick Data*

Let's follow the process using an empirical simulation. We sample intra-day prices of an EUR/USD option on currency futures with six different strike prices. These are derivative contracts that grant the purchaser the right, but not the obligation, to trade a currency futures contract; which is a contract to exchange two currencies at an agreed-upon exchange rate at a certain point in the future. Our data sample consists of trade and quote data of four weeks available from 13 August 2012 to 17 September 2012 (expiry date) from the Chicago Mercantile Exchange (CME). The options data is available from 13 August 2012 to 7 September 2012, due to the prior expiry of options to final settlement or expiration of the underlying futures contract. The quote data contains trade prices, bid and ask prices and volumes. A UNIX timestamp in milliseconds records the date and the time at which the quote originated. Table D.1 shows number of tick data and price ranges.

Due to the high-frequency character of tick data, we match the nearest futures quote or available trade price to the relevant option price. Figure D.4 show the generated cleared data sets of underlying futures prices, option prices and correspondent option premiums.

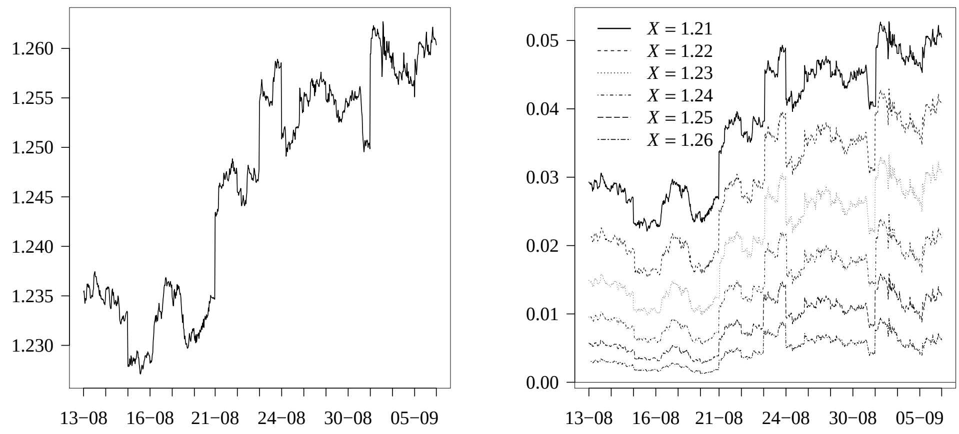
The dataset period starts with a relatively low exchange rate and converges to a new high to maturity. Therefore, we can see that all option prices are in-the-money at the end of the period. In contrast to option prices, the option premiums converge to zero. This is explained by the remaining trading time.

Table D.1: Dataset of six EUR/USD FX options on futures (underlying) with different strike prices in the period from 13 August 2012 to 7 September 2012[a]

	Option Strike Price					
Measure	$X = 1.21$	$X = 1.22$	$X = 1.23$	$X = 1.24$	$X = 1.25$	$X = 1.26$
N Ticks (raw)	45,890	43,990	54,904	43,669	29,928	14,271
N Ticks (cleared)	12,000	12,000	12,000	12,000	12,000	12,000
. . . OTM Options	0	0	567	2,143	2,209	7,050
. . . ITM Options	12,000	12,000	11,433	9,857	9,791	4,950

[a] OTM means out-of-the-money options, whereas ITM are in-the-money options.

Figure D.4: Underlying EUR/USD futures prices, EUR/USD FX options and correspondent option premiums for six different strike prices



(a) Futures Prices F_t

(b) Call Option Prices C_t

Nevertheless, data collection at high-frequency on financial markets requires the manipulation of complex databases and possibly the correction of errors present in the data. Several studies investigated methods for cleaning tick data - see Dunis et al. (1998) and Brownlees and Gallo (2006) for further details. After data cleaning, we remove randomly tick data to get workable sets for our experimental design.

For purpose of training, each data set is divided into several subsets. First, we separate an out-of-sample. In real life this would be the next trading day after overnight computing. The in-sample runs from 13 August 2012, 09:30 p.m. GMT to 05 September 2012, 02:15 p.m. GMT. This implies that we get a sample of 60,000 ticks observations for the estimation period and a sample of 12,000 observations for the out-of-sample period - a typically ratio of 5 to 1. Second, we divide our in-sample set in a training and a validation set. Conforming to standard heuristics, the

Figure D.5: Separation in training, validation and out-of-sample generalization sets

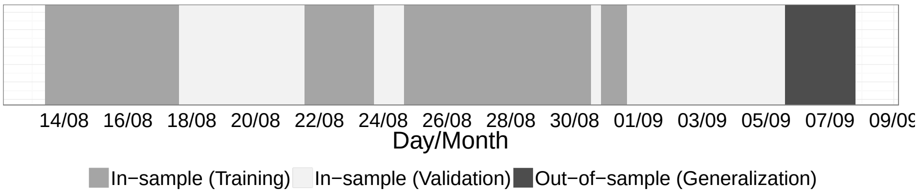


Table D.2: NN approximation performance of option market prices with different network topologies (1000 successfully computed networks)[a]

	Network Topology					
Measure	A	B	C	D	E	F
# Hidden neurons n_h	1	2	3	4	5	8
Computing time (hours)	1.02	1.55	2.33	3.15	3.79	5.17
Training error ε_t	12.6206	4.0805	4.0462	6.5290	8.6431	17.2267
Training error ε_v	15.5087	5.1262	5.0778	8.2530	10.2904	17.5376
RMSE $\times$ 100	0.0368	0.0243	0.0234	0.0297	0.0760	0.0999
Adjusted $\bar{R}^2$	0.9927	0.9972	0.9973	0.9954	0.9848	0.9521

[a] Note, that the errors increase with more than three hidden neurons. To achieve better results with higher neurons we might increase the number of successfully trained networks (1000).

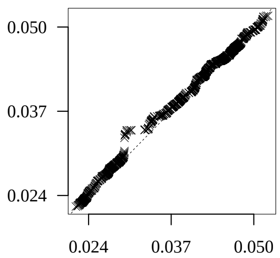
training and validation sets were partitioned approximately 2.7 to 1 - see figure D.5 for an illustration of the sample sets.

4.2 *Simulation Results*

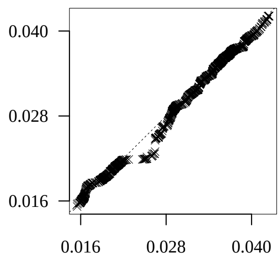
Now, we are ready for training all input variables over the initial period to generate heuristic (model) premiums for each strike price simultaneously. We do several simulations with different network topologies and simulation steps to analyze error accuracy and computing performance time. Due to the restricted post-trade horizon for back-testing our FDSS (overnight), we first reject network specifications, which exceed a prescribed computing time. We achieve accurate and stable results with 1000 simulation steps or trained networks. Second, we have to find the best topology in order to minimize the training and validation error. In general, this is achieved by comparison of the best trained network in each simulation study. To reduce erratic oscillations and to improve accuracy we smooth the training results by averaging the best 20 trained networks. In table D.2 we present accuracy criteria for different topologies.

The results are encouraging in the sense that we get a good fit of the data, although we train six long time series simultaneously. Regarding our data sample, the topology C with three hidden neurons shows the best accuracy. All heuristic option premiums computed by this "winning" network topology are shown in figure D.6. We can see that the network prices can approximate market prices with high degree. However, it is important to know that the approximation performance of OTM options achieve worse results. Due to the minority of OTM option data, it seems to be an exhausting balancing act for the NN to train options with higher strike prices more accurately (last subfigure D.6f). In addition, we observe a heavily price jump of the EUR/USD exchange rate on the 21th August (ECB news regarding the debt crisis in the euro zone). This explains the outliers in all subfigures.

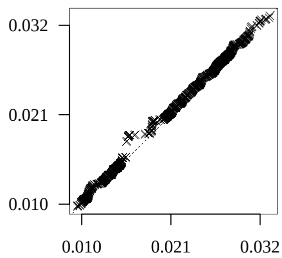
Figure D.6: Quantile-quantile plot of fitted (model) and observable option market prices



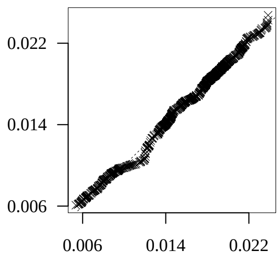
(a) Strike $X = 1.21$



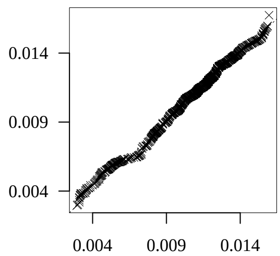
(b) Strike $X = 1.22$



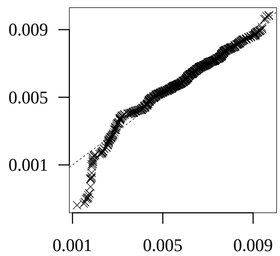
(c) Strike $X = 1.23$



(d) Strike $X = 1.24$



(e) Strike $X = 1.25$

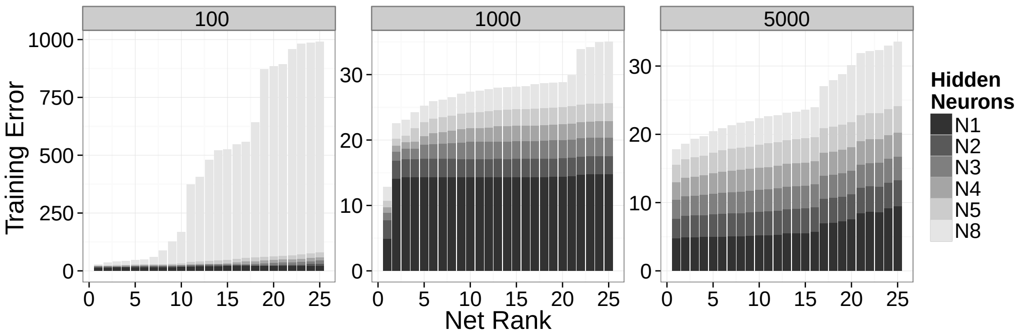


(f) Strike $X = 1.26$

The computing time does not exceed the overnight time in all topologies. In general, the error decreases with higher number of trained networks (figure D.7). We have parallel trained all topologies on a compute server with 2×4 cores (2 $\times$ CPU Intel Xeon E5420 @ 2.50 GHz) and 16 GB RAM. Topologies with only one or more than 5 hidden neurons seems to be not perform as well as the other topologies.

Our network algorithm c_t^{NN} (see formula D.4 in section 3.2) for option pricing and live trading is now parameterized and is ready for implementation in the live trading engine. Computing of option prices with this algorithm takes fractions of a second. All option market prices can be compared to single out overpriced and underpriced ones for each timestamp. Hence, network evaluation is almost instantaneous even in a high-frequency context.

Figure D.7: Best 25 single training errors of topologies A-F (hidden neurons 1-5 and 8) for 100, 1000 and 5000 successfully trained networks



4.3 *Evaluation and Limitations*

We outline steps towards a high-frequency FDSS for pricing options and conduct an experimental study with empirical data. While the experimental results are encouraging, we also have to take some limitations into account. We are at now not able to confirm the robustness, validity and performance of a NN-based FDSS in general. However, our experimental results give us useful hints and motivation to enhance the developed FDSS. In table D.3 we outline three major clusters of critical questions, limitations or possible enhancements.

At this point we would like to emphasize on further investigations with alternative option pricing models or methodologies. In case of option on currency futures we might benchmark our model with Black's option pricing model. Furthermore, hybrid model construction with NN and closed-form option pricing models is another interesting object of investigation. We expect that an interaction of these different model types could achieve reliable results. However, the parallel or hybrid use of different option pricing methodologies might be an attractive but complex enhancement.

5 CONCLUSIONS AND MANAGEMENT RECOMMENDATIONS

In this paper we present steps towards a model-driven financial decision support model (FDSS) to pricing option on currency futures, which can be embedded in a high-frequency trading process. To develop an appropriate FDSS, we use the design science methodology of Hevner. We identify problem relevance in the field of pricing options in financial markets, and suggest needs for efficient FDSS for high-frequency trading processes.

We propose a heuristic option pricing model with powerful neural networks (NN) to synthesize the option premium for all call FX option. NN exhibit several benefits: They are suitable for solving non-linear problems like approximation of option prices, and we only need available tick data without any assumptions,

Table D.3: Major clusters of critical aspects, limitations or possible enhancements

Selection of data

- Need for tests over a longer time horizon (this provide longer out-of-sample periods)
- Need for investigations with a wider range of option data dimensions (e.g. overlapping option series with different expiry or option prices under different market conditions)
- Taking other input variables into account could increase accuracy (e.g. volatility and interest rates)

Selection of model

- Need for benchmarking with different NN model types (e.g. recurrent neural networks)
- Integration of further methods like out-of-sample pricing or hedging strategies
- Need for accurate model parametrization θ

Usability aspects

- The present FDSS prototype does not feature a graphical user interface (GUI)
- Re-training networks during run-time high-frequency trading might be time-critical in case of extraordinary market scenarios
- Precluding more complex and granular models in favour of model performance from a usability view

which leads to a manageable model. Furthermore, NN is able to train different option series simultaneously. This paper mostly presents the model-driven FDSS as a high-frequency pricing-decision tool. We implement NN as a core engine in a high-frequency trading process. To evaluate its usability we start an experimental design with empirical tick data of EUR/USD options on currency futures. The results are encouraging in the sense that it provides accurate market prices for six different strike prices simultaneously. If the market and heuristic prices differ significantly we can take this as a signal that an option is currently either too cheap or too expensive. We are now able to answer our research question in the following way:

- Neural networks are a suitable core engine for a model-driven FDSS embedded in a high-frequency trading process and can support trading decisions.
- While post-trade network training is a computing-intensive issue, run-time evaluation of ensembles takes fractions of a second and is therefore instantaneous in a high-frequency context.

Nevertheless, we outline critical limitations and thinkable extensions in order to design further steps towards an efficient FDSS for option pricing applications. In our view the most important aspect is to test the model on a wider range of overlapping option series with different expiry dates. This will allow us to better gauge the practical applicability of our FDSS. With our approach it is not difficult to adapt to other underlying time series. We expect the model to react robustly and to generalize well in daily use. We hope that these further steps allow us to conclude that our FDSS for currency option pricing is an artifact that "extends the boundaries of human problem solving" (Hevner et al. (2004)).

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THE »PRICING OPTIONS« PAPER

Pricing and Forecasting of High-Frequency Options on Currency Futures with Fast Neural Networks

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ABSTRACT

Due to the difficulty of option valuation, we provide an alternative model-free option pricing approach with neural networks, which can be embedded in a high-frequency trading process. An essential advantage of our approach is the simultaneous pricing across different strike prices and parsimonious use of input variables. To achieve this, we conduct an empirical run-time trading simulation with a tick data set of EUR/USD options on currency futures of four weeks. In non-overlapping 15 minutes out-of-sample intervals theoretical option prices derived from the Black model compete against nonparametric option prices through neural network models. We show that the use of neural networks is suitable in generating fast run-time option pricing evaluation as their pricing accuracy is comparable to theoretical prices. Due to the used implied volatility the Black model persists slightly superior. Nevertheless, we also have to take particular limitations into account, which give us useful hints for further research and steps.

KEYWORDS

Option Pricing, Neural Networks, Options on Currency Futures, High-Frequency Data

JEL C45, C52, C61, C63, G12

Pricing and Forecasting of High-Frequency Options on Currency Futures with Fast Neural Networks

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1 INTRODUCTION

Since the introduction of electronic brokers in the foreign exchange (FX) interbank market in 1992, the FX options market is a vast subject. Advances in computer technology and automated algorithm trading have supercharged the transmission and execution of orders, making use of the big data – and established a new phenomenon: "high-frequency trading" (HFT). Nowadays, market participants need access to the speed, liquidity and pricing accuracy of FX option products for hedging or speculative purposes. Thus, an accurate market valuation of option products in the HFT FX market is still difficult and needs appropriate models and techniques (Aldridge (2010)).

Option pricing is based on theoretical models developed by Black and Scholes (1973), Merton (1973) and Cox et al. (1979) with several extensions. In each case, the derivation of the pricing formula depends intimately on the particular parametric form of the underlying asset's price dynamics $S(t)$. A misspecification of the stochastic process for $S(t)$ will lead to systematic pricing and hedging errors for derivatives. Therefore, the success or failure of the traditional approach to pricing and hedging options is closely tied to the ability to capture the dynamics of the underlying asset's price process. Despite usefulness of closed-form type models, Black (1975), Rubinstein (1985) and Bakshi et al. (2000) emphasized that some models primarily address perceived weaknesses. Unfortunately theoretical pricing models are based on several unrealistic assumptions. First of all, markets are efficient, i.e., nobody can consistently predict the direction of the market or an individual underlying. Secondly, underlying prices follow a memoryless continuous-time or discrete-time stochastic process. In addition, the future volatility σ of the underlying price can be estimated accurately and is a priori known to seller and buyer of an option. Permanently an unsatisfactory and quite artificial adaption to the true market conditions is necessary.

Hence, nonparametric or model-free pricing methods for pricing and hedging derivatives attempt to overcome the mentioned restrictions in theoretical models.

As option pricing theory typically derives non-linear relations between an option price and the variables determining it, neural networks (NN) are well suited for this purpose due to their ability to approximate any measurable function up to an arbitrary degree of accuracy. Rather than starting from a price process of the underlying security and subsequently deriving the corresponding option value, the option market's pricing mechanism is estimated from observed prices via a NN. When properly trained, the network "becomes" the option pricing formula, which may be used in the same way that formulas obtained from the parametric pricing method are used: for pricing, delta-hedging, simulation exercises, etc. Network-based models have several important advantages over the more traditional parametric models. First, since they do not rely on restrictive parametric assumptions such as lognormality or sample-path continuity. Second, they are adaptive and respond to structural changes in the data-generating processes and robust to specification errors that plague parametric models. Of course, the nonparametric pricing method is highly data-intensive, requiring large quantities of historical prices to obtain a sufficiently well-trained network. Therefore, such an approach would be inappropriate for thinly traded derivatives, or newly created derivatives.

Much has been written about option market price synthesis with NN since first attempts in the 1990ies. For a detailed current overview about the range of prior studies see Chen and Sutcliffe (2012). Many of these studies maintain the view that NN models are capable of generating better results in comparison to closed-form models like the Black-Scholes (BS) formula in pricing options. Pioneers are Malliaris and Salchenberger (1993) and Hutchinson et al. (1994), who compared the performance of the BS model and NNs in pricing American-style call options. They found that NNs were preferable, but in some regimes, i.e. for out-of-the-money options, the BS performed better. Boek et al. (1995) and Lajbcygier et al. (1997) proposed hybrid neural networks, which combine theoretical option models with NNs. This nested models often exceeds the performance of other models. In the following, Anders et al. (1998), Garcia and Gençay (2000), Andreou et al. (2002) and Bennell and Sutcliffe (2004) got similar encouraging results with European-style options. While many studies were motivated in using historical or realized volatility estimates for the theoretical model specification, other alternative volatility estimates are rare, e.g. Amilon (2003) and Andreou et al. (2006) extended their investigation with the use of implied volatilities. Furthermore, subsequent studies mostly investigated daily equity index options data for option pricing approximations with NNs. Despite the high liquidity of FX options markets, there is no noticeable investigation about pricing FX options with NN in a HFT-context. In general, Dunis and Serpinis (2011) concluded that NN models do have the ability to forecast EUR/USD returns for the period investigated. Recent research dedicated to the performance of HFT is concentrated on volatility patterns and forecasts - see Andersen and Bollerslev (1997), Andersen et al. (2003), McMillan and Speight (2012), McMillan and Garcia (2013) and Matias and Reboredo (2012).

Thus, we see a lack of further investigations in option market price synthesis with NN - especially in case of HFT markets. Here, we propose a model-free method for estimating the pricing formula of FX options with different strike prices using learning networks. We build on these prior investigations, but we augment our study with a run-time trading process to uncover special characteristics of high-frequency data. The benefits of our NN technology as a kind of core engine allows option sellers and buyers to approximate call option prices across different strike prices simultaneously and with parsimonious input specification. In particular, we pose the following challenge: if option prices were truly determined by the theoretical model exactly, can the closed-form formula for different strike prices be estimated nonparametrically by NN with a sufficient degree of accuracy to be of practical use? Furthermore, can both models be implemented in an automatic HFT process, where a signal must be precise enough to trigger trades in a fraction of a second? To assess the potential value of network pricing formulas in HFT, we simulate theoretical option prices and show that learning networks can recover the closed-form formula from a four week training set of intra-day EUR/USD options prices on currency futures. Some reasons for the popularity of options on futures are that options on futures generally require less investment than options on the physical good itself. We implement a rolling 15 minutes out-of-sample interval for each trading day to assess the models pricing ability. The specification of all NN models is used as in Breitner (2000), were options with different strike prices are put into one network input. The results are then benchmarked with Blacks model (Black (1976)) for pricing options on futures.

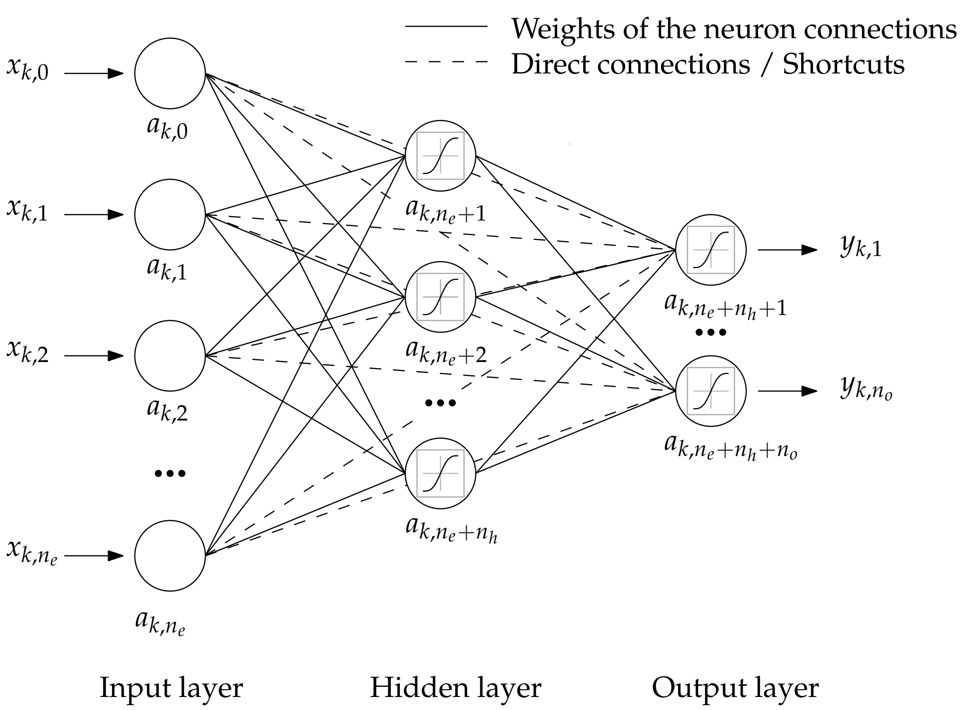
We organize this paper as follows: First, we introduce our NN methodology for applications in a high-frequency process. Next, we propose the mentioned option pricing models for pricing options on futures: a closed-form model of Black, two NNs and a hybrid approach. in section four we explain the data preprocessing step, which is essential for handling high-frequency data. In section five we conduct an experiment with empirical tick data of EUR/USD options on currency futures and analyze the results. In addition, we outline limitations of our work. The paper finishes with a brief conclusion, and summarizes the results.

2 METHODOLOGY

Neural Networks are known as universal approximatiors, since they can interpolate a large variety of unknown mappings, once a training sample is given. Since it is our goal to extract an alternative option pricing formula from the market observations, we focus on multilayer perceptron (MLP), which are applicable to non-linear regression problems. An alternative network is the so-called radial basis function (RBF) network. A general introduction in NN for market application is described in Priddy and Keller (2005), Wang (2005) and Li and Ma (2010). Although both network types have the universal approximation capability and are therefore well suited for modelling option prices, here we deal exclusively with the MLP type of neural networks. We follow the argumentation of Anders et al. (1998) and Hornik et al. (1990), that feedforward networks with only one hidden layer and a linear output unit are able to approximate simultaneously its unknown derivatives up to an arbitrary degree of accuracy. This characteristic is substantial since the partial derivatives of a pricing formula are needed for the hedging of option positions, a subject of similar importance as the pricing itself.

The basic process units of NN architecture are neurons which are internally in connection with neurons from subsequent layers. Firstly, the inputs (x_k) are fed to the input layer, the outputs (y_k) are given in the output layer, and in between, there is an arbitrary number of hidden neurons. Inputs and outputs (x_k, y_k) represent a training pattern k. The network used in our study is a single hidden-layer feedforward NN - see figure E.1 for illustration.

Figure E.1: Exemplarily 3-layered perceptrons



Exemplarily 3-layered perceptrons with shortcut connections have an auxiliary neuron N_0 (bias neuron) with $x_{k,0} \equiv \frac{1}{2}$, where $k = 1, 2, \ldots, n_p$ and n_p denotes the number of training and validation patterns, with input neurons $N_1, \ldots, N_{n_e}$, with hidden neurons $N_{n_e+1}, \ldots, N_{n_e+n_h+1}$ (N_{n_e+1} is the auxiliary bias neuron in the hidden layer), where n_h is the number of hidden neurons and $n_h \geq 1$, with output neurons $N_{n_e+n_h+2}, \ldots, N_{n_e+n_h+n_o+1}$ and with the hyperbolic tangent transfer function tanh. Enabled 3-layered perceptrons are defined by

$$a_{k,i} := x_{k,i} \qquad \text{for} \quad i = 0, 1, \ldots, n_e, \tag{E.1}$$

$$a_{k,i} := \tanh\left(\sum_{j=0}^{n_e} a_{k,j} w_{j,i}\right) \quad \text{for} \quad i = n_e + 1, \ldots, n_e + n_h, \tag{E.2}$$

$$a_{k,i} := \tanh\left(\sum_{j=0}^{n_e+n_h} a_{k,j} w_{j,i}\right) \text{for} \quad i = n_e + n_h + 1, \ldots, n_e + n_h + n_o. \tag{E.3}$$

N_i's output for pattern (x_k, y_k) is denoted by $a_{k,i}$. Note the missing bias neuron in the hidden layer: it can be omitted, because with shortcut connections enabled the bias neuron in the input layer influences the output neurons.

The ability of NNs to process depends on connections which are named as weights w. The weights give the abilities of prediction or classification to the system. Firstly, the inputs (x_k) fed to the input layer are weighted and summed up. Then they are entered to an activation function in order to get an output from each neuron. The weights are iteratively changed until the best loads are obtained. To find the right weights within a so-called training process thousands of multi-layer perceptrons with various topologies and with different weight initializations are trained. All weights $w_{j,i}$ of the weight matrices $W_{12} \in \mathbb{R}^{n_h+1, n_e+1}$ (input layer $\rightarrow$ hidden layer) and $W_{23} \in \mathbb{R}^{n_o, n_h+1}$ (hidden layer $\rightarrow$ output layer), are trainable except w_{0,n_e+1}. For shortcuts $W_{13} \in \mathbb{R}^{n_o, n_e+1}$ exists analogously and the bias neuron in the hidden layer is omitted.

To avoid over-fitting we employ the cross-validation technique. The idea of cross validation is to split the training set into two: a set of examples to train with I_t, and a validation set I_v. Out-of-sample pricing on the validation set is used to determine which model to use, in which the error of the validation set is a minimum. Training a neural network amounts to choosing its biases and weights w_{ij} to minimize accuracy criterion, e.g. the least squares of the observable output. The approximation quality of the NN can be estimated with the training and validation error functions. These are given for $n_o = 1$ by

$$\varepsilon_t := \frac{1}{2} \sum_{k \in I_t} \left(a_{k,n_e+n_h+1} W - y_k\right)^2 \quad \text{and}$$

$$\varepsilon_v := \frac{1}{2} \sum_{k \in I_v} \left(a_{k,n_e+n_h+1} W - y_k\right)^2.$$

For $n_o > 1$ a sum over all output neurons must be taken. As usual the perceptron is trained iteratively, i.e., ε, is decreased by adaption of W, as long as $\varepsilon_v < \varepsilon_t$ or $\varepsilon_v \approx \varepsilon_t$ holds. Both training and validation error are exclusively affected by the used topology, i.e. number of inner neurons and shortcuts activation. Prior studies of related research have shown that a three-layer network can be trained to approximate most functions arbitrarily well. Network architectures with more than three layers only sometimes lead to significant enhancements.

In case of HFT, computational requirements should be high and require special high performance computers. We do our network training with the FAUN (Fast Approximation with Universal Neural Networks) neurosimulator. As described in Mettenheim and Breitner (2010) two reasons make FAUN suitable for HFT. First, the FAUN neurosimulator uses fine-grained parallelization. This allows easily achieved speedups on dual and quad core CPUs. FAUN also features coarse-grained parallelization using an easy to install grid computing client. It is possible to use clusters of heterogeneous workstations. Second, using reverse accumulation and matrix algorithms make a very efficient computation possible.

3 OPTION PRICING MODELS

3.1 *Closed-form Option Pricing Formula*

To judge the pricing accuracy of network pricing, the performance of the NN needs to be measured against an alternative model. In this study the Black model (BL) is used for this purpose, which produces a closed-form expression of the option price. We prefer the Black model instead of the standard Black-Scholes model, because we are able to relax the assumption about continuous dividend payouts. Furthermore, the Black model is used for pricing options on futures, which is our objective here. Despite the fact that both basis theoretical models are generally not used in its original form in practice, we focus on it here because it is still a widely used benchmark model, and it is easily applicable in practice.

According to Black (1976), the derivation of the Black model relies on the following assumptions. Asset prices follow a geometric Brownian motion, mean returns and volatilities are constant over time, interest rates are both constant over time and equal for all maturities, trading occurs continuously on frictionless markets and no arbitrage opportunities exist. From these premises Black derived the following formula for the price of a European call option written on a futures contract:

$$C_{\mathrm{BL}}(t) = F(t)\Phi(d_1) - Xe^{-r\tau}\Phi(d_2), \tag{E.4}$$

where

$$d_1 = \frac{\ln(F(t)/X) + (r + \sigma_F^2/2)\tau}{\sigma\sqrt{\tau}}$$

$$d_2 = d_1 - \sigma_F\sqrt{\tau}$$

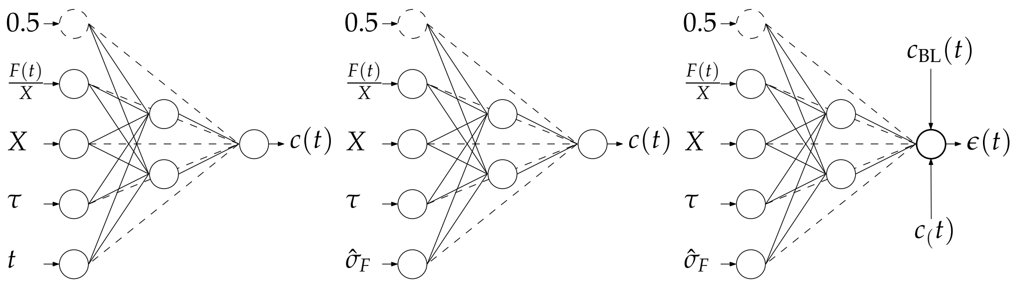
and $\Phi(\cdot)$ is the cumulative probability function for a standardized normal variable. Following equation E.4 the theoretical fair call option price C_{BL} depends on five input parameters: the underlying futures price $F(t)$, the strike price X, the time to expiration or live of an option $\tau = T - t$, the risk-free interest rate r up to expiration and the asset volatility σ_F of the underlying price. The Black formula is similar to the Black-Scholes formula except that the spot price of the underlying $S(t)$ is replaced by a futures price $F(t)$.

Among parameters described above, the standard deviation σ_F of the returns during the life of the option can not be known in advance and consequently an estimate is required. There is no consensus on the appropriate method for estimating standard deviation of the price series. Further, it is a common knowledge that σ_F of the price series varies with time. An alternative method is to estimate a so called implied volatility that minimizes option pricing error in previous transaction. In particular, there can be at most one value for σ_F that, when applied as an input to $f(\sigma_F, \tau, F(t), X, r)$ will result in a particular value for $C(t)$. Assume that there is some inverse function $g = f^{-1}$, such that $\hat{\sigma}_F = g(C(t), \cdot)$. The value $\hat{\sigma}_F$, is the volatility implied by the market price or the implied volatility. In general, it is not possible to give a closed form formula for implied volatility in terms of call price. Many studies documented presence of systematic biases in implied volatility measures. As a result, $\hat{\sigma}_F$ often oscillates erratically and closed-form formulas captures not the option market conditions. The measure often exhibits an U-shape curve which is known as volatility smile. Nevertheless, implied volatilities yield often to better results than other techniques like historical or realized volatility estimates. In our study, we calculate the implied volatility for the last in-sample market price for each option. These values are then treated as an input variable for volatility parameter in calculations of the theoretical out-of-sample options price for the Black model with the implied volatility for the next observation.

3.2 *Empirical Option Pricing based on Neural Networks*

In contrast to the theoretical pricing models, an empirical model-free pricing model based on highly accurate neural network approximations can learn true market pricing of options. We test two alternative topologies. The first is a parsimonious specified model NN I, which relax the estimation of r and σ_F. Like the theoretical option price $C_{\mathrm{BL}}(F(t), X, \tau, r, \sigma_F)$, this empirical option price $C_{\mathrm{NN\,I}}(F(t)/X, X, \tau, t)$ depends only on the permanently available moneyness $F(t)/X$, which is the quotient of the underlying price F and the option's strike price X, the strike price X itself and the time to expiration τ. Instead of r and the artificially estimated $\hat{\sigma}_F$, we use the permanently available trading day t as direct input for the empirical pricing model. Note that $t \in \mathbb{R}^+$ enables a continuous-time model and an intra-day option pricing. Inputs and output of the NN must be carefully transformed and equilibrated to facilitate the neural network training. Our second topology NN II replaces the trading time t by the implied volatility $\hat{\sigma}_F$ to investigate the volatility influence. Rubinstein (1985) found that implied volatility is a function of moneyness $F(t)/X$ and time to expiration τ. Hence, the empirical option price $C_{\mathrm{NN\,II}}(F(t)/X, X, \tau, \hat{\sigma}_F)$ depends on four input variables. Due to the intra-day character, there is no need for incorporation of the risk-free interest rate r. Figure E.2a and figure E.2b illustrate the proposed NN topologies.

Figure E.2: NN topologies (three-layered perceptron) with variable number of hidden neurons used for market price synthesis



(a) Network topology NN I **(b)** Network topology NN II **(c)** Network topology BL+NN

Due to performance reasons, we transform all output market prices $C(t)$ in option market premiums

$$c(t) = \frac{X + C(t) - F(t)}{F(t)}, \tag{E.5}$$

which can be easily re-computed to option prices. In summary, the NN architecture used in this study is a feed-forward network with three layers. The first layer includes the four major influencing variables $F(t)/X, X, \tau$ and t (NN I) or $\hat{\sigma}_F$ (NN II) of a call option price. The second layer has a varying number of hidden neurons. The third layer contains only the trained options' market premium $c(t)$.

3.3 *Empirical Option Pricing based on Hybrid Neural Networks*

In a fourth pricing formula the Black model is nested in a NN - a so called hybrid model (BL+NN). We refer to prior investigation like in Boek et al. (1995) to combine the Black model and NN and then test its validity. The basis of the hybrid approach to the problem is in using the Black model as a base, and allowing the NN to augment its performance. The values of $F(t), X, \tau$ and $C(t)$ are obtained from past market option information, and the interest rate and volatility can be estimated or approximated as desired. Essentially, the network has $F(t)/X, \tau, r$ and σ_F presented as inputs, and the difference between the Black model and the $C(t)/X$ value taken from the real data presented as targets. The network is thus trained to produce an appropriate deviation from the Black according to the input parameters as shown in figure E.2c above. Therefore, when the system is used for pricing, the difference between the theoretical and the network output should produce the appropriate estimated $C(t)/X$ value. This leads to the following price quotation:

$$c_{\mathrm{BL+NN}}(t) = c_{\mathrm{BL}}(t) + \epsilon(t), \tag{E.6}$$

where $\epsilon(t)$ means the trained difference between the theoretical pricing formula and the observable market option price. It is an advantage of the hybrid model that those parts of the pricing mechanism which are already explained by the theoretical formula need not to be approximated by the network. When the Black model provides reasonable results the network can concentrate on the differences between theoretical and observed prices. If estimation errors are reduced, the out-of-sample accuracy of the pricing formula should improve.

4 DATA

We sample intra-day prices of an EUR/USD option on currency futures with five different strike prices. These are derivative contracts that grant the purchaser the right, but not the obligation, to trade a EUR/USD futures contract; which is a contract to exchange EUR and USD at an agreed-upon exchange rate at a certain point in the future. Further details to options on futures are described in Ball and Torous (1986) and Broadie et al. (2007). Our data sample consists of trade and quote futures data of four weeks available from 13 August 2012 to 17 September 2012 (expiry date) from the Chicago Mercantile Exchange (CME). The options data is available from 13 August 2012 to 7 September 2012, due to the prior expiry of options to final settlement or expiration of the underlying futures contract. The data contains trade or quote prices, bid and ask prices and volumes. A UNIX timestamp in milliseconds records the date and the time at which the quote originated.

Due to the high-frequency character of tick data, we match the nearest futures quote or available trade price to the relevant option price. For high-frequency data cleaning it is necessary to implement automatic procedures based on some criteria in order to decide on the possible elimination of each observation. First, in order to remove uninformative and non-representative option records we employ exclusion criteria similar to those of Rubinstein (1985); Sheikh (1991); Xu and Taylor (1994) and Barndorff-Nielsen et al. (2009). We carefully check, that the lower boundary condition for the value of European call options is not violated, which is binding for all European-style options independent of a specific option pricing model. Furthermore, we have no option, which is deep-in- or deep-out-of-the-money. Those options are traded roughly at their intrinsic value and have almost no informational content. Second, we consider an algorithm proposed by Dunis et al. (1998); Brownlees and Gallo (2006) and Mineo and Romito (2007), that verifies the validity of an observation on the basis of its relative distance from a neighborhood of the closest valid observations, based on the following rule. Let $\{C_i\}_{i=1}^{N}$ be an ordered tick-by-tick price series.

$$(|C_{\{i\}} - \bar{C}_{\{-i\}}(l)| < 3s_{\{-i\}}(l) + \varphi) = \begin{cases} \text{true} & \text{observation } i \text{ is kept} \\ \text{false} & \text{observation } i \text{ is removed} \end{cases} \tag{E.7}$$

where $\bar{C}_i(l)$ and $s_i(l)$ denote respectively the mean and the standard deviation of a neighborhood of l observations around i without the i-th observation and φ is the granularity parameter. The granularity parameter is considered because the ultra high-frequency series often contain sequences of equal prices which would lead to a zero variance. Third, trading volume and the volatility of the market diminish significantly during weekends and holidays as shown by Bollerslev and Domowitz (1993). To eliminate weekend or thinly traded times effect, we concentrate on the most liquid daily trading period between 12:00 and 16:00 GMT from Monday to Friday and exclude a London Summer Bank Holiday (27 August) and the USA Labour Day (03 September). We further replace those options, which has less than two days to maturity. This criterion is used to eliminate options with a short time to maturity, as these options have only a small time-value, which can lead to severe deviations when calculating theoretical option prices. Table E.1 summarizes the cleared number N of tick data.

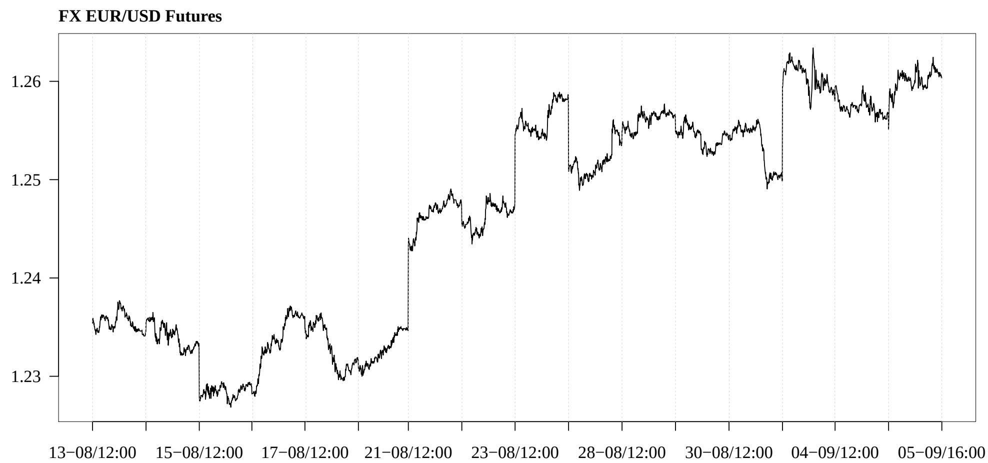
Table E.1: Number of ticks in the whole trading simulation period

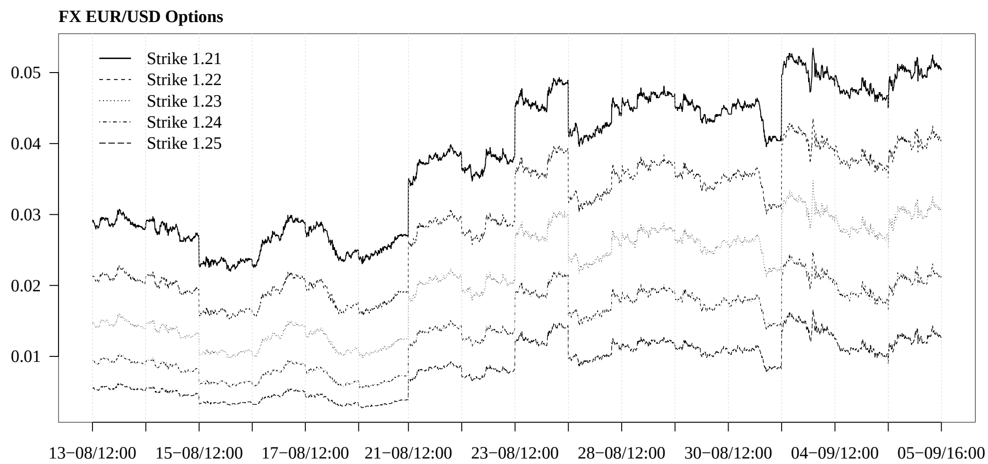
		Single Options				
	Overall	$X = 1.21$	$X = 1.22$	$X = 1.23$	$X = 1.24$	$X = 1.25$
N	105, 160	26, 140	23, 548	25, 343	18, 791	11, 338

Figure E.3 shows the generated cleared data sets of underlying futures and correspondent option prices. The dataset period starts with a relatively low exchange rate and converges to a new high to maturity. Therefore, we can see that all option prices are in-the-money at the end of the period. In contrast to option prices, the option premiums converge to zero. This is explained by the remaining trading time. In order to calculate an adequate interest rate r which matches the time to maturity for each option, we linearly interpolated the neighbouring interest rates and transformed the resulting values into compounded rates. Our interest rate data consist of daily interbank rates (US LIBOR) for overnight, one week, two week and one month money.

We are now ready to specify our trading simulation strategy. Our objective is to investigate the run-time pricing accuracy of a closed-form option pricing model and a model-free NN in a HFT process. Hence, we implement an intra-day rolling out-of-sample pricing, i.e. the first in-sample for training purposes runs from 12:00 GMT to 12:30 GMT (30 minutes) followed by the first out-of-sample from 12:30 GMT to 12:45 GMT (15 minutes). The second in-sample starts from 12:15 GMT to 12:45 GMT followed by the second out-of-sample from 12:45 GMT to 13:00 GMT and so on. Thus, we get 14 non-overlapping 15 minutes out-of-sample intervals till we reach the end of our daily trading period at 16:00 GMT. The next trading day starts with a new training set. For purpose of training, we divide all in-sample sets in a training and a validation set. Conforming to standard heuristics, the training and validation sets were partitioned approximately 4 to 1.

Figure E.3: Underlying EUR/USD futures prices and options for five different strike prices





For illustration purposes we force the asynchronously series to a synchronized and equispaced one minute time grid by taking the last price realized before each grid point.

In contrast to prior studies we conduct a simultaneous training over the initial period to generate empirical option prices for each strike price simultaneously. Note, that prices are typically not recorded at equispaced time points. Both the theoretical and NN model impose no requirements to the record set, which is in contrast for statistical estimations. Therefore, we keep all observations in each sample as they occur. Thus, the number of each option varies during the trading simulation in each sample.

5 RESULTS

5.1 *Optimal Network Topologies*

We do several simulations with different network topologies and simulation steps to analyze error accuracy. Due to the restricted in-sample training horizon for pricing the next 15 minutes, we first reject network specifications, which exceed a prescribed computing time. We achieve accurate and stable results with 2000 successfully trained networks. Second, we have to find the best topology in order to minimize the training and validation error. In general, this is achieved by comparison of the best trained network in each simulation study. To reduce erratic oscillations and to improve accuracy we smooth the training results by averaging the best 10 trained networks. For all three mentioned network models we choose two hidden neurons, which leads to accurate results while the computation time will be controllable. Once an appropriate network has been found, computing of option prices with this network takes fractions of a second. All option market prices can be compared to single out overpriced and underprized ones for each timestamp. Hence, network evaluation is almost instantaneous even in a high-frequency context.

5.2 *Out-of-sample Pricing Accuracy*

It still remains to be examined how far the different network specifications and volatility estimates lead to good out-of-sample pricing performance. To compare the observed market prices $C(t)$ with those obtained from the models $\hat{C}(t)$, the following measures of fit were computed:

$$\begin{aligned}
\bar{R}^2 \quad &= 1 - \frac{T-1}{T-p-1}\frac{\sum_{i=1}^{T}(C(t)-\hat{C}(t))^2}{\sum_{i=1}^{T}(C(t)-\bar{\hat{C}}(t))^2},\\
\text{ME} \quad &= \frac{1}{T}\sum_{t=1}^{T}(C(t)-\hat{C}(t)),\\
\text{RMSE} \quad &= \sqrt{\frac{1}{T}\sum_{t=1}^{T}(C(t)-\hat{C}(t))^2},\\
\text{MAPE} \quad &= \frac{1}{t}\sum_{t=1}^{T}\left|\frac{C(t)-\hat{C}(t)}{C(t)}\right|,\\
\text{Theil's } U &= \sqrt{\frac{\sum_{t=1}^{T}(C(t)-\hat{C}(t))^2}{\sum_{t=1}^{T}(C(t)-\hat{C}_{BL}(t))^2}}.
\end{aligned}$$

The adjusted $\bar{R}^2$ measures the correlation between the observed market prices and fitted option prices, while the mean error (ME) indicates a pricing bias. Since the network models are estimated by using the sum of squared errors, it is obvious to evaluate the models with the Root Mean Squared Error (RMSE), which gives absolute measures of price discrepancy. In addition, we calculate the mean absolute percentage error (MAPE), which has the advantage of being scale independent, so they are frequently used to compare forecast performance between different data series. However, MAPE is sometimes criticized, because it is infinite or undefined if there are zero values in a series. The Theil's U represents a relative measures, which measures how well the model performs against a "naive" model - in our case the Black model. Theil's U-Statistic scales the RMSE by the variability of underlying data and has the advantage of being independent of the variance of the actual process. If U is more than one, the NN does not beat the "naive" Black model.

When looking on the out-of-sample pricing performance in table E.2 we see that pricing errors from the observed market prices are quite small. It is interesting that the Black model achieves encouraged results, which is a little bit surprising in view of prior studies. Nevertheless, all models fit the observed market prices very well. The theoretical option prices from the Black model are quite similar for all strike prices. For the empirical derived prices it seems that a simultaneous training of five different strike prices would lead to some less accurate prices for higher strike prices. This could be accounted for by the different moneyness in these options, which is in line with prior investigations - e.g. Malliaris and Salchenberger (1993) found that BS was preferable for in-the-money options. At the beginning of our trading period options with higher strike prices are out-of-the money.

Additional observations are worth pointing out: while the incorporation of the implied volatility in the NN model does not achieve appreciable performance improvements, the hybrid model does not improve the theoretical option model. We assume that the simultaneous training is reasonable for this surprising aspect.

Table E.2: Statistical out-of-sample pricing accuracy for all strike prices[a]

			Strike X				
Model	Measure	Overall	1.21	1.22	1.23	1.24	1.25
BL	$\bar{R}^2$	0.9999	0.9999	0.9998	0.9992	0.9995	0.9990
	ME $\times 100$	0.0009	0.0008	-0.0011	0.0031	0.0004	0.0010
	RMSE $\times 100$	0.0119	0.0108	0.0122	0.0155	0.0090	0.0084
	MAPE	0.3086	0.1792	0.2379	0.3480	0.3744	0.5567
	Theil's U	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NN I	$\bar{R}^2$	0.9998	0.9999	0.9997	0.9991	0.9971	0.9932
	ME $\times 100$	-0.0022	0.0023	-0.0032	-0.0057	-0.0062	0.0036
	RMSE $\times 100$	0.0172	0.0117	0.0144	0.0178	0.0221	0.0218
	MAPE	0.5167	0.1810	0.2751	0.4964	0.8316	1.3165
	Theil's U	1.4377	1.0822	1.1815	1.1443	2.4449	2.5770
NN II	$\bar{R}^2$	0.9997	0.9999	0.9997	0.9971	0.9982	0.9884
	ME $\times 100$	-0.0003	0.0009	-0.0023	-0.0026	-0.0022	0.0077
	RMSE $\times 100$	0.0196	0.0107	0.0131	0.0306	0.0168	0.0287
	MAPE	0.5093	0.1817	0.2848	0.5783	0.6325	1.3718
	Theil's U	1.6407	0.9963	1.0778	1.9712	1.8563	3.3946
BL+NN	$\bar{R}^2$	0.9998	0.9997	0.9995	0.9982	0.9988	0.9974
	ME $\times 100$	-0.0003	-0.0008	-0.0011	0.0005	0.0000	0.0006
	RMSE $\times 100$	0.0179	0.0161	0.0182	0.0231	0.0139	0.0132
	MAPE	0.4944	0.3001	0.3877	0.5487	0.5770	0.9058
	Theil's U	1.4985	1.4922	1.4937	1.4860	1.5348	1.5658

[a] The table shows the pricing accuracy for the options on currency futures with five different strike prices X in the period 13 August to 06 September 2012 (16 trading days).

It is obviously an exhausting balancing act for the NN to train five different option series simultaneously. Hence, it would be interesting to compare single trained network results. When the NN concentrates only on a particular option series we would expect an improvement of performance measures in case of the hybrid model. Furthermore, we show the NN's difference in the RMSE to the Black model and the Theil's U for each trading day in table E.3. Except the hybrid model, the NN results seem not to be very accurate in the beginning of the trading period. For the rest the results are comparable.

In summary, the results are encouraging in the sense that we get a good fit of the data, although we train five long time series simultaneously. The density plots of out-of-sample differences between market and model prices (figure E.4) show comparable results. Model-free based option prices derived from NN can synthesize option market prices in a similar manner, but in a simultaneous way and with a more parsimonious input specification. E.g., there is no need of volatility or interest estimation.

Table E.3: Statistical out-of-sample pricing accuracy for each trading period[a]

		NN I		NN II		BL+NN	
	Period	Δ RMSE[b]	Theil's U	Δ RMSE	Theil's U	Δ RMSE	Theil's U
1	2012-13-08	0.0055	1.9052	0.0334	6.4690	0.0041	1.6768
2	2012-14-08	0.0135	2.9407	0.0133	2.9090	0.0029	1.4157
3	2012-15-08	0.0081	1.9665	0.0099	2.1830	0.0057	1.6771
4	2012-16-08	0.0029	1.3810	0.0016	1.2064	0.0021	1.2761
5	2012-17-08	0.0051	1.4749	0.0048	1.3741	0.0070	1.5528
6	2012-20-08	0.0048	1.4333	0.0033	1.2553	0.0063	1.6215
7	2012-21-08	0.0012	1.1865	0.0019	1.2901	0.0054	1.7905
8	2012-22-08	0.0060	1.8453	0.0023	1.3228	0.0057	1.7940
9	2012-23-08	0.0083	1.8864	0.0002	1.0250	0.0071	1.7608
10	2012-24-08	0.0021	1.1627	0.0016	1.1208	0.0039	1.3058
11	2012-28-08	−0.0093	0.5183	0.0014	1.0701	0.0103	1.5317
12	2012-29-08	0.0036	1.4864	0.0055	1.7494	0.0028	1.3842
13	2012-30-08	0.0142	2.4443	0.0062	1.6316	0.0053	1.5339
14	2012-31-08	0.0007	1.0313	0.0051	1.2586	0.0086	1.4381
15	2012-05-09	0.0005	1.0690	0.0008	1.1027	0.0033	1.3961
16	2012-06-09	0.0041	1.4340	0.0002	1.0275	0.0054	1.5690

[a] The table shows the pricing accuracy for the options on currency futures with five different strike prices X for each considered trading day.

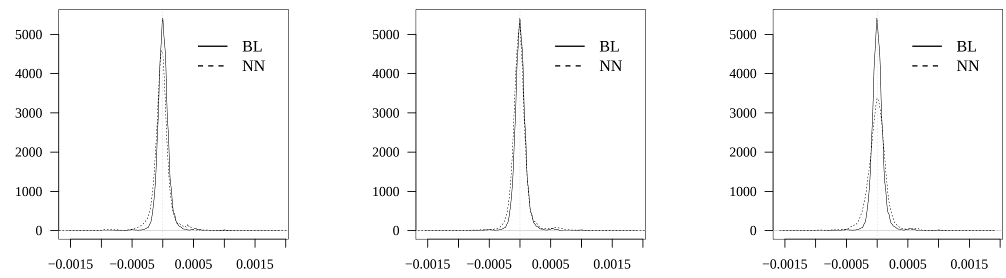
[b] We show the RMSE difference to the benchmark model (BL). Positive values indicate a lower RMSE for the benchmark model.

Nevertheless, even the proclaimed naive Black model adapts accurately observable market prices in short intra-day periods and achieves an outstanding performance. For our data sample, we conclude that market participants may orientate themselves towards theoretical option models in short intra-day periods. In contrast to prior studies we work out two essential differences: first, our trading horizon (15 minutes) is very short, which leads to small deviations. Second, the choice of the volatility estimate plays an important role for theoretical option pricing models. Prior studies often use historical or realized volatility estimations. Thus, we assume that the implied volatility estimator is an outstanding volatility estimator for short-term out-of-sample pricing.

5.3 *A brief Outlook on further Research*

From this point of investigation further research steps are thinkable and we recommend three particular aspects. First, as mentioned above we could relax our NN specification of simultaneous option pricing. We would expect, that the NN captures better the pricing path and pricing accuracy would improve. Second, the statistical significance of out-of-sample option pricing is difficult to formulate be-

Figure E.4: Density of pricing errors



(a) BL vs. NN I **(b)** BL vs. NN II **(c)** BL vs. BL+NN

cause the errors in fitting the option prices are likely to be correlated across options and over time. Usually, we would use the Diebold and Mariano test (Diebold and Mariano (1995)), which assumes that the sequence of the difference between the predictions of two models is covariance stationary. But Amilon (2003) noted, that in case of option pricing the Diebold and Mariano test statistic is not an appropriate test. He recommended a moving block bootstrap to test the statistical significance. Therefore, we would extend our study with an appropriate significance test. Third, as option pricing models are frequently used to calculate hedge parameters, it is necessary to check whether the parameters obtained from the NNs are reliable insofar as they follow certain patterns suggested by theory. The very essence of all parametric continuous-time pricing formulas is the ability to replicate an option through a dynamic hedging strategy. To be of any practical relevance, the NN models must also be able to hedge an option position. Of primary interest are the hedging parameters or Greek letters resulting from the pricing model. They are defined as follows:

$$\Delta = \frac{\partial C(t)}{\partial F(t)}, \quad \Theta = \frac{\partial C(t)}{\partial (T-t)}, \quad \Gamma = \frac{\partial \Delta}{\partial F(t)}$$

where delta (Δ) and theta (Θ) are the partial derivatives of the option price with respect to changes in the futures price and the time to maturity, while gamma (Γ) gives the sensitivity of delta with respect to changes in the futures price. Hence, a calculation of hedge parameters in order to further validate our models seems to be necessary.

6 CONCLUSIONS

In this paper we propose an empirical option pricing model with powerful neural networks (NN) to synthesize FX option prices. NNs exhibit several benefits: they are suitable for solving non-linear problems like approximation of option prices, and we only need available tick data without any assumptions, which leads to a manageable model. Furthermore, NN is able to train different option series simultaneously. This paper mostly presents the NN as a run-time pricing tool for options, which can be implemented in a HFT process. In particular, option pricing evaluation is difficult, due to the weakness of theoretical pricing models.

To evaluate its usability we conduct an experimental trading simulation with empirical tick data of EUR/USD options on currency futures. We specify several NN topologies: first, a parsimonious network, which relax the parametrization of the risk-free interest rate and volatility of the underlying asset. Second, we include the last observable in-sample implied volatility and third, we implement a hybrid theoretical and NN model. The last one attempt to uncover the pricing differences between the theoretical and observable market price. To judge the pricing accuracy of all models we benchmark it with the closed-form Black model for pricing option on futures. A continuous risk-free interest rate is derived from market data and the volatility parameter is set by the last observable in-sample implied volatility. We implement an intra-day 15 minutes rolling out-of-sample pricing in the daily time period from 12:30 GMT to 16:00 GMT. Thus, we get 14 non-overlapping 15 minutes out-of-sample intervals till we reach the end of our daily trading period. The next trading day starts with a new training set.

The results are encouraging in the sense that it provides accurate market prices for five different strike prices simultaneously. Although parametric pricing formulas are slightly better, our results show that nonparametric learning-network alternatives can be useful substitutes. Nevertheless, we outline critical limitations and thinkable extensions in order to design an augmented HFT trading simulation with NNs. This includes training option prices separately to achieve a better performance and implementing a significance test. While the accuracy of the learning network prices is obviously of great interest, this alone is not sufficient to ensure the practical relevance of our nonparametric approach. In particular, the ability to hedge an option position is as important, since the very existence of an arbitrage-based pricing formula is predicated on the ability to replicate the option through a dynamic hedging strategy.

F

THE »FORECASTING FREIGHT RATES I« PAPER

Freight Rates in the Tanker Shipping Market – Short-Term Forecasting of Spot Rates and Derivatives with Linear and Non-Linear Methods

Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2012). *Freight Rates in the Tanker Shipping Market - Short-Term Forecasting of Spot Rates and Derivatives with Linear and Non-Linear Methods.* Paper presented at the 19th Annual Meeting of the German Finance Association (DGF), Hannover, Germany, October 05-06, 2012.

ABSTRACT

In this paper we investigate the forecasting and trading performance of linear and non-linear methods, in order to generate short-term forecasts of spot freight rates and corresponding freight derivatives respectively Forward Freight Agreements (FFA) in the dirty tanker shipping market. We attempt to uncover the benefits of using several time series models and the potential of neural networks. Maritime forecasting studies using neural networks are rare and only focus on spot rates, with the result that only longer forecasting horizons lead to encouraging results with neural networks. We build on this kind of investigation, but we extend our study on freight rates derivatives or FFA prices and a wider range of time series models. Before we implement a simple trading simulation in order to evaluate the predicted freight rates, we compare the statistical forecasting performance of all models. Our conclusion is, that non-linear methods like neural networks are suitable for short-term forecasting and trading spot freight rates and freight derivatives, as their results match or improve on those of other models. Nevertheless, we think that further research with freight rates and corresponding derivatives is developable for decision and trading applications with enhanced forecasting models.

KEYWORDS

Shipping Freight Market, Neural Networks, Forward Freight Agreement (FFA), Forecasting Performance, Trading Performance

JEL C45, C53, G13, G14, G17

Freight Rates in the Tanker Shipping Market – Short-Term Forecasting of Spot Rates and Derivatives with Linear and Non-Linear Methods

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1 INTRODUCTION

In this paper we investigate the forecasting and trading performance of non-linear forecasting models, to generate short-term forecasts of spot rates and corresponding freight forwards respectively Forward Freight Agreements (FFA) in the dirty tanker shipping market. In recent time freight derivatives become interesting in the maritime market due to the fact, that freight rates are very volatile. Derivative markets provide a way in which these risks may be transferred to other individuals who are willing to bear them, through hedging. The main objective of the established FFA market was to provide a mechanism for hedging of freight risk in the dry-bulk and wet-bulk shipping sector. Nevertheless, due to the high volatility of freight rates, actors in the shipping market are forced to use forecasting techniques for the purpose of risk management.

Freight rates exhibit certain characteristics in the class of commodities: The freight rate represents as an underlying asset a transport service and can be classified as non-storable commodity like electricity. This means, that there is no arbitrage between spot and forward freight rates. Therefore, spot and forward freight rates are not related to the cost-of-carry relationship. Forward prices are unbiased predictors for future spot prices in the class of non-storable commodities in speculative-efficient markets. Thus changes in forward prices are affected by new information in this market. But the low liquidity in the FFA market and the until now almost non-existence of speculative interests lead to the fact, that forward rates do not exhibit these properties. In contrast to other established markets, only a small number of actors operate in the FFA market and it is not sure that all relevant information is contained in the forward price. The non-existence of arbitrage in the FFA market leads to the fact, that the spot rate converges to the forward rate, because the forward rate contains certain information about future spot rates. There is no reason, why the forward rate should converge to the spot rate.

Most studies on forecasting freight rates use traditional time series models and focus on statistical forecast performance measures, e.g. Culliane (1992), Culliane et al. (1999) and Veenstra and Franses (1997). Kavussanos and Nomikos (2003) and Batchelor et al. (2007) compared a range of time series models in forecasting spot freight rates and freight forward contracts respectively FFA rates. They concluded, that freight forward contracts are suitable to detect the tendency of future spot freight rate, but FFA rates do not seem to be helpful in predicting the direction of future spot rates. In addition, Alizadeh and Nomikos (2003) showed that FFA rates do not seem to be helpful in predicting the direction of future spot rates. The latter studies exhibit the common characteristic that the forecasting accuracy declines as maturity increases.

However, the use of linear time series models for freight rates is sometimes criticized, due to the fact that most financial time series show non-linear patterns (see Adland and Cullinane (2006) and Goulielmos and Psifia (2009)). As a representative of non-linear methods, neural networks could be implemented for several financial applications. Li and Parsons (1997) were the first, who used neural networks in their investigation of spot freight rates. They pointed out that neural networks can significantly outperform simple time series models for longer-term forecasting of monthly tanker spot freight rates. Also, Lyridis et al. (2004) attempted to investigate the advantages of neural networks in predicting spot freight rates of large oil carrier (VLCCs). In their opinion neural networks are superior for investigations of non-stationary and non-linear time series. A more recent study of Mettenheim and Breitner (2010) shows that neural networks achieve good forecasting and trading results in predicting the Baltic Dry Index (BDI), which measures the cost to haul dry freight over the world's oceans. According to trading investigations of freight rates and derivatives some examples and details are given by Alizadeh and Nomikos (2009).

Nevertheless, we find a lack of jointly spot and forward forecasting investigations with neural networks. We build on these investigations, but we extend our study on freight derivatives and a wider range of time series models. The main objective of this paper is to investigate neural networks' prediction ability for maritime business forecasting and provide a practical framework for actual forecasting and trading applications of neural networks. The investigation occurs in two steps: First, we implement a performance test of several forecasting models in predicting spot freight rates and FFA prices. The main objective is to reduce forecasting error in variance. Typically, modeling techniques are optimized using a mathematical criterion, but ultimately the results are analyzed on a financial criterion upon which is not optimized. In other words, the forecast error may have been minimized during model estimation, but the evaluation of the true merit should be based on the performance of a trading simulation. Hence, we evaluate our forecasting results in a simple trading simulation, which is a better indicator for trading purposes than forecasting performance measures.

The paper is organized as follows. Section 2 gives a short introduction about the methodology of neural networks and alternative statistical time series models. Section 3 describes the data and our forecasting strategy. After specifying and estimation of time series and neural network models in section 4 we generate one-step ahead predictions of spot freight rates and freight derivatives in section 5. In a further step we evaluate these statistical performance results in a simple trading simulation (section 6). Finally, Section 7 summarizes our conclusions.

2 FORECASTING MODELS

In this paper we apply several forecasting techniques for our investigation. We introduce both traditional linear time series models and a neural network as a representative for non-linear models.

2.1 *Linear Time Series Models*

In general, we can separate time series models in univariate and multivariate time series classes in case of their input observations. Thus a univariate time series refers to a single sequence of observations.

Auto-Regressive Integrated Moving Average (ARIMA) models are a general class of univariate models to find the best fit of a time series to past values of this time series, in order to make forecasts. They were popularized by Box and Jenkins (1970). The ARIMA model, also often called Box-Jenkins model, assumes that the time series is stationary. Box and Jenkins recommend differencing non-stationary series one or more times to achieve stationarity. We get our ARIMA$(p, 1, q)$ model - in our case for one spot freight rate and two FFA contracts with different maturities:

$$\begin{aligned}
\Delta\hat{S}_t &= \alpha_s + \sum_{i-1}^{p} \alpha_{s,i}\Delta S_{t-i} + \sum_{i-1}^{q} \beta_{s,i}\epsilon_{s,t-i} + \epsilon_{s,t}, \quad \epsilon_{s,t} \sim iidN(0, \sigma_s^2) \\
\Delta\hat{F}_{1,t} &= \alpha_1 + \sum_{i-1}^{p} \alpha_{1,i}\Delta F_{1,t-i} + \sum_{i-1}^{q} \beta_{1,i}\epsilon_{1,t-i} + \epsilon_{1,t}, \quad \epsilon_{1,t} \sim iidN(0, \sigma_1^2) \\
\Delta\hat{F}_{2,t} &= \alpha_2 + \sum_{i-1}^{p} \alpha_{2,i}\Delta F_{2,t-i} + \sum_{i-1}^{q} \beta_{2,i}\epsilon_{2,t-i} + \epsilon_{2,t}, \quad \epsilon_{2,t} \sim iidN(0, \sigma_2^2)
\end{aligned}$$

Where $\Delta\hat{F}_t$ and $\Delta\hat{S}_t$ are log returns of spot freight rates and FFA prices, respectively, and the ϵ_t are random error terms. To identify the appropriate ARIMA model for a time series, there are three primary stages in building a Box-Jenkins time series model: first, we have to identify the order(s) of differencing needing to stationarize the series. The primary tools for doing this are the autocorrelation plot and the partial autocorrelation plot. Second, we have to estimate the parameters for the Box-Jenkins model. At least, model validation ensures to fit the most appropriate model. Typically, effective fitting of Box-Jenkins models requires at least a moderately long series.

Correspondingly to univariate time series models, a multivariate time series refers to a sequence of vectors of observations. Statistical multivariate time series methods include the Vector Auto-Regressive process (VAR) and the Vector Error Correction model (VECM). A VAR model, first advocated by Sims (1980), is an econometric model used to capture the evolution and the interdependencies between multiple time series, generalizing the univariate models. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. Thus our corresponding VAR(p) model with lag-length p is:

$$\Delta\hat{S}_t = \alpha_s + \sum_{i-1}^{p} \alpha_{s,i}\Delta S_{t-i} + \sum_{i-1}^{p} \beta_{s,i} F_{1,t-i} + \sum_{i-1}^{p} \beta_{s,i} F_{2,t-i} + \epsilon_{s,t}$$

$$\Delta\hat{F}_{1,t} = \alpha_1 + \sum_{i-1}^{p} \alpha_{1,i}\Delta S_{t-i} + \sum_{i-1}^{p} \alpha_{1,i}\Delta F_{1,t-i} + \sum_{i-1}^{p} \beta_{1,i} F_{2,t-i} + \epsilon_{1,t}$$

$$\Delta\hat{F}_{2,t} = \alpha_2 + \sum_{i-1}^{p} \alpha_{2,i}\Delta S_{t-i} + \sum_{i-1}^{p} \alpha_{2,i}\Delta F_{1,t-i} + \sum_{i-1}^{p} \beta_{2,i} F_{2,t-i} + \epsilon_{2,t}$$

The potential advantage of the multivariate VAR model according to the univariate ARIMA model is that it takes into account the information content in the spot price movement in determining the forward price and vice versa.

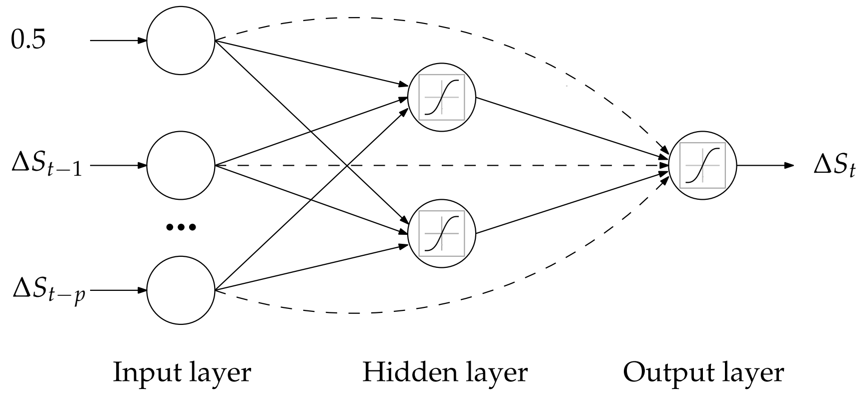
In case of non-stationarity modelling, multivariate time series are complicated. The cointegration approach of Engle and Granger (1987) is a helpful tool in this case, which means that a particular linear combination of the non-stationary variables are stationary. Then the variables are said to be cointegrated. Therefore, we extend the VAR model by equilibrium correction terms, which represents the cointegrating (long-run) relationship between the spot freight rates and FFA prices. The VECM leads often to more satisfactory results than ARIMA and VAR models as both the short-run dynamics and the long-run relationship between variables are taken into account.

2.2 *Non-linear Neural Network Model*

Neural networks (NN) can be described as non-linear input-output models. They provide the basis for an entirely different approach to the analysis of time series. The connections between inputs and outputs are typically made via one or more hidden layers of neurons, sometimes alternatively called processing units or nodes. NN also appear to have potential application in time series modelling and forecasting. Nevertheless, the success of NN modelling depends on a suitable topology or architecture. This includes determining the number of layers, the number of neurons in each layer and which variables to choose as inputs and outputs. The number of hidden layers is often taken to be one, while the number of hidden neurons is found heuristically. In the case of time series prediction, feedworward NN use the past lagged observations as inputs to conduct one or multi-step ahead forecasts.

They do not require any assumptions relating to the underlying data-generating process. Figure F.1 shows an example of a neural network topology for time series forecasting purposes.

Figure F.1: Topology of a typical NN for time series forecasting



Example with one hidden layer of two neurons. The output, e.g. the forecast variable, depends on the lagged input values at times $t-1, \dots, t-p$.

In our case, a one-step ahead forecast of spot freight rates returns $\Delta\hat{S}_t$ is computed using lagged input variables $(\Delta S_{t-1}, \Delta S_{t-2}, \dots, \Delta S_{t-p})$ as follows (for FFA prices in the same manner):

$$\Delta\hat{S}_t = f(\Delta S_{t-1}, \Delta S_{t-2}, \dots, \Delta S_{t-p}), \tag{F.1}$$

where f denotes the function determined by the network. Thus the NN is equivalent to the nonlinear autoregressive model for time series forecasting problems. One of the input variables will usually be a constant. The neural network attempts to find the best possible approximation of the function f as a complex combination of elementary non-linear functions. This approximation is coded in the neurons of the network using weights that are connected with each neuron. These weights effectively measure the 'strength' of the different connections and are parameters that need to be estimated from the given data. We further assume there are H neurons in one hidden layer and then attach the weight w_{ij} to the connection between input S_{t-i} and the jth neuron in the hidden level. Given values for the weights, the value to be attached to each neuron may then be found in two stages. First, a linear function of the inputs is found:

$$net_j = \hat{w}_o + \sum_i^p w_{ij} \Delta S_{t-i} \tag{F.2}$$

for $j = 1, 2, \dots, H$. Second, the quantity net_j is converted to the final value for the jth neuron by applying an activation function - in our case we use the hyperbolic tangent, $\tanh(net_j)$. Having calculated values for each neuron, a similar pair of operations can then be used to get the predicted value for the output using the values at the H neurons. This requires a further set of weights $\hat{w}_j$ to be attached to the links between the neurons and the output. Overall the output $\Delta\hat{S}_t$, is related to the inputs by the following expression:

$$\Delta\hat{S}_t = f_o\left[\left(\sum_j \hat{w}_j \tanh\left(\sum_i^p w_{ij}\Delta\hat{S}_{t-i}\right) + \hat{w}_o\right)\right], \tag{F.3}$$

where f_o denotes the activation functions at the output layer. It is also easy to incorporate further input variables into NN model. In this case, we are able to extend such an univariate NN to a multivariate topology.

3 DESCRIPTION OF DATA AND FORECASTING STRATEGY

A forward freight agreement (FFA) is an agreement between two counterparties to settle a freight rate or hire rate, for a specified quantity of cargo or type of vessel, for one or a basket of major shipping routes in the dry-bulk or the tanker markets at a certain date in the future. The underlying asset of FFA contracts is a freight rate assessment for an underlying shipping route. On the tanker side, you have many contracts - tanker FFAs routes are centralized around the biggest physical routes for shipments of crude oil, known as trade dirty (TD) or trade clean (TC) followed by a numeral to designate the vessel size and cargo. The most liquid routes are TD3, TD5, TD7 and TC2. We sample daily prices of the International Maritime Exchange (Imarex) TD3 and TD5 freight forward contracts - see table F.1 for more details. The Imarex is a hybrid exchange, where standardized contracts are traded and cleared. These contracts are written on daily spot rates for TD3 and TD5 published by the Baltic Exchange. The spot and FFA data is available from 5 April 2004 to 1 April 2011.

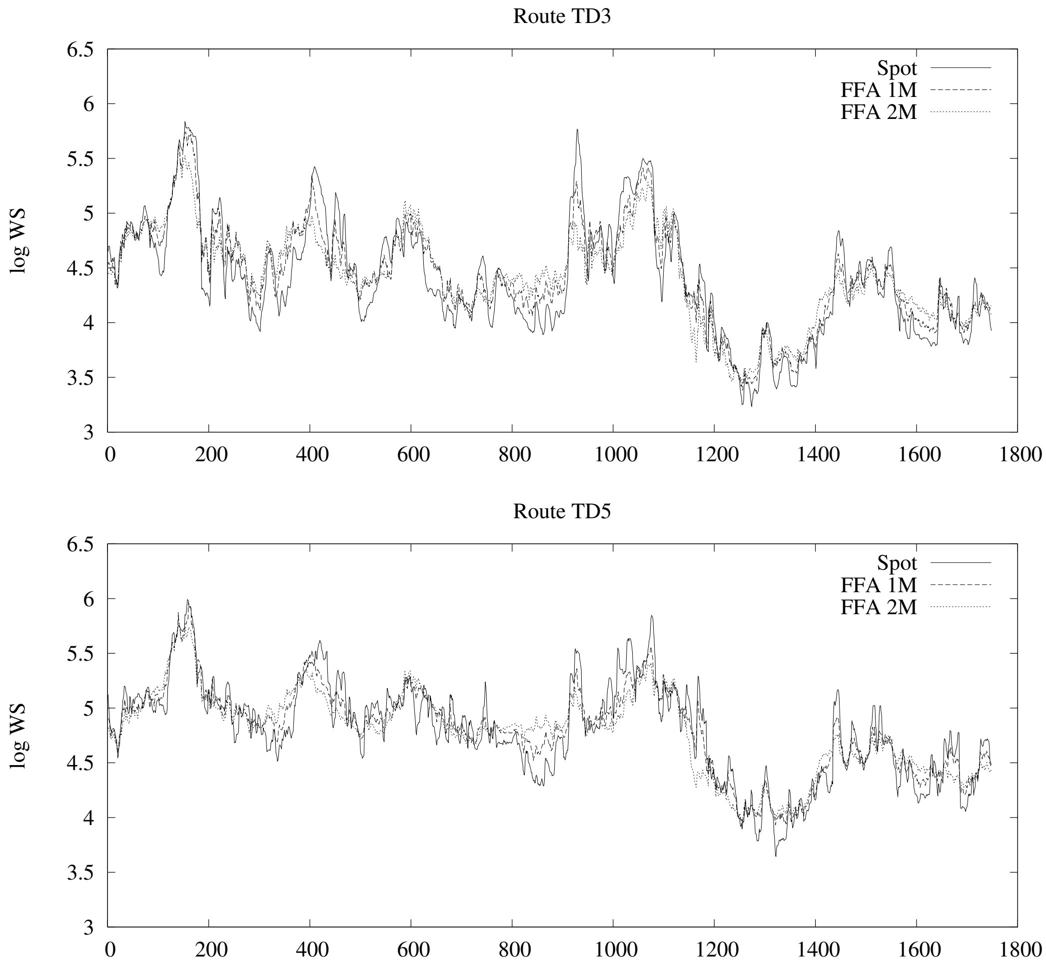
Table F.1: Overview of the relevant freight forward contracts

Route	Trade[a]	Size[b]	Lot size	Price quotation[c]
TD3	VLCC, Middle East to Japan	260,000 mt	1000 mt	WS points
TD5	Suezmax, West Africa to US East Coast	130,000 mt	1000 mt	WS points

[a] Vessel classes: Suezmax - an ocean-going cargo vessel of the maximum size possible to pass through the locks of the Suez Canal in Egypt. Very Large Crude Carrier (VLCC) - an ocean-going crude oil tanker of 200,000 to 299,999 dwt.
[b] mt means miles per ton.
[c] WS denotes Worldscale points - a unified system of establishing payment of freight rate for a given oil tanker's cargo.

To avoid expiry effects, we calculate "perpetual" forward contract for one month (22 trading days; FFA 1M) and two month (44 trading days; FFA 2M) as a weighted average of a near and distant futures contracts, weighted according to their respective number of days from maturity. This procedure generates a series of futures prices with constant maturity and avoids the problem of price-jumps caused by the expiration of a particular futures contract. Figure F.2 shows all data points. We can see typical patterns of spot rates and FFA prices: When the spot market is at a relatively low level, the forward rates increase with time to maturity; in other words the forward curve is in contango, indicating the anticipation of the market of future increases in the spot rates. On the other hand, when the spot market is at a high level, the forward curve is downward sloping, or backwarded, thus indicating the anticipation of the market of lower freight rates in the future. This pattern in forward curves is consistent with the mean reversion property of freight rates.

Figure F.2: Spot and forward prices for TD3 and TD5



All prices are transformed to natural logarithms. Summary statistics of logarithmic first-differences ("log returns") of daily spot and FFA prices are presented in table F.2 for the whole period in the two dirty tanker routes. The result's excess kurtosis in all series, and the skewness does not necessarily imply a symmetric distribution. The Jarque-Bera tests indicate departures from normality for both spot and FFA prices in all routes. This seems to be more acute for the spot freight rates. The Ljung-Box $Q(12)$ statistic on the first 12 lags of the sample autocorrelation function and Engle's ARCH test indicate significant serial correlation and existence of heteroscedasticity, respectively. In contrast to storable commodities, such as stocks, there is no reason to expect changes in spot freight to be serially uncorrelated. Demand and supply for freight services are determined by the needs of trade.

Augmented Dickey Fuller (ADF) and Phillips-Peron (PP) unit root tests on the log levels and log first-differences of the daily spot and FFA price series indicate that all variables are log first-difference stationary, but the levels indicate, that most price series follow unit root processes. ADF and PP tests are sometimes criticized for their lack of power in rejecting the null hypothesis of a unit root when it is false. This lack of power is addressed by the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test, which has stationarity as the null hypothesis. Furthermore, the results of the Brock, Dechert and Scheinkman (BDS) test strongly suggest that the time series in all contracts are non-linearly dependent, which is one of the indications of chaotic behavior.

For purpose of forecasting, each data set is divided into two subsets: the first subset runs from 5 April 2004 to 16 February 2010, the second subset from 17 February 2010 to 1 April 2011. The first subset is used to estimate the statistical models and identify the neural network structure while the second is used only for out-of-sample prediction comparison. This implies that we get a sample of 1466 daily observations for the estimation period and a sample of 282 daily observations for the forecasting period - a ratio of 5.25 to 1. The estimation period starts with a relatively higher rate. Both freight rates reached abruptly their highest level at the end of the year 2004. The forecasting period includes the years of lower rates.

4 ESTIMATION RESULTS AND MODEL SPECIFICATION

We separate all models in univariate and multivariate model classes: the univariate models consist of an ARIMA and a NN model, where we include only the relevant single spot or FFA time series. For the multivariate models VAR, VECM and a multivariate neural network, namely NN+, we include both spot and all FFA rates of each route. As noted above, the results of the unit root tests on the log levels and log first-differences of the daily spot and FFA price series indicate that all variables are log first-difference stationary, all having a unit root on the log levels representation. This means that the first-differences of spot and forward series should be used, while cointegration tests should be performed to ascertain the long-run relationship between the series if the VECM model is going to be used. Johansen's multivariate cointegration test (Johansen, 1988) results indicate that spot and FFA prices are cointegrated in all routes (see table F.3).

Table F.2: Descriptive statistics[a]

	TD3			TD5		
	Spot	FFA 1M	FFA 2M	Spot	FFA 1M	FFA 2M
N[b]	1747	1747	1747	1747	1747	1747
Mean (levels)	4.41	4.44	4.43	4.80	4.81	4.78
SD (levels)	0.52	0.45	0.41	0.44	0.39	0.37
Skew (levels)	0.38	0.13	−0.06	−0.06	−0.12	−0.13
Kurtosis (levels)	−0.12	−0.01	−0.13	−0.24	−0.09	−0.22
Jarque-Bera[c]	10212.88***	1146.48***	1482.50***	9560.54***	1966.65***	1581.69***
Ljung-Box[d]	974.58***	179.33***	120.73***	465.72***	140.06***	90.27***
ARCH[e]	115.64***	126.99***	176.95***	21.90	105.88***	73.31***
ADF[f]	−18.32***	−24.77***	−26.33***	−22.09***	−25.52***	−26.11***
ADF (levels)	−3.78***	−2.72*	−2.39	−4.10***	−2.25	−1.65
PP	−22.56***	−31.79***	−33.73***	−25.81***	−32.56***	−34.80***
PP (levels)	−3.53***	−2.59	−2.19	−3.57	−2.13	−1.67
KPSS	0.02***	0.03***	0.04***	0.01***	0.03***	0.05***
KPSS (levels)	0.23	0.27	0.28	0.28	0.34	0.35
BDS[g]	16.02***	11.53***	11.34***	7.75***	6.92***	6.36***

[a] The table shows descriptive statistics for the log differences of spot and FFA rates. Data are daily in the period 5 April 2004 to 1 April 2011.

[b] N shows the number of daily observations. Skewness and kurtosis are estimated centralized third and fourth moments of the data.

[c] The Jarque-Bera test for normality is distributed as $\chi^2(2)$, with a critical 5% value of 5.9915. $*$, $**$ and $***$ denote the significance level at 10, 5 and 1%.

[d] Q(12) is the Ljung and Box Q statistics on the first 12 lags of the sample autocorrelation function with a critical 5% value of 51.48.

[e] ARCH(12) is the test for the 12th-order autoregressive conditional heteroscedasticity. The 5% critical value for this statistic is 1.81.

[f] ADF is the Augmented Dickey and Fuller test. The ADF regressions include an intercept term; the lag length of the ADF test is determined by minimizing the AIC. PP is the Phillips and Perron test, and KPSS the Kwiatkowski, Phillips, Schmidt, and Shin test. The 5% critical value for the ADF and PP tests is -2.89, and the 5% critical value for the KPSS test is 0.146.

[g] BDS is the Brock, Dechert and Scheinkman test for non-linearity with embedding dimensions $m = 3$. The null hypothesis of this test is that the data is an independently and identifically distributed (iid) process versus general non-linearity in the series. The 5% critical value for the BDS tests is 1.96.

Table F.3: Johansen tests for the number of cointegration vectors[a]

Hypothesis		Test statistic λ_{max}		Hypothesis		Test statistic λ_{trace}		95% critical val.	
H_0	H_1	TD3	TD5	H_0	H_1	TD3	TD5	λ_{max}	λ_{trace}
$r = 0$	$r = 1$	62.4386	104.2255	$r = 0$	$r > 0$	95.0499	137.3461	22.00	34.91
$r = 1$	$r = 2$	27.2815	28.5986	$r = 1$	$r > 1$	32.6113	33.1206	15.67	19.96
$r = 2$	$r = 3$	5.3298	4.5219	$r = 2$	$r > 2$	5.3298	4.5219	9.24	9.24

[a] r represents the number of cointegrating vectors. $\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ and $\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the $\prod$ matrix. Critical values are from Osterwald-Lenum (1992).

The estimation results of all models for spot and FFA rates for the two routes is presented in the following table F.4.

The lag length for the autoregressive and moving average parts are chosen to minimize the Akaike information criterion (AIC). As expected, the adjusted coefficients of determination for the multivariate models are in most cases slightly higher than those of the univariate models due to the use of extra information, namely, the lagged FFA rates in the spot equation and vice versa. All models seem to be well specified, as indicated by relevant diagnostic tests.

Conforming to standard heuristics, the training and validation sets of our neural networks were partitioned approximately 2.7 to 1. The training set runs from 5 April 2004 to 14 July 2008 (1066 observations) and the validation set runs from 15 July 2008 to 16 February 2010 (398 observations), identical to the in-sample period for the benchmark models. To start, traditional linear partial autocorrelation function can give some indication about significant lag structures for the input variables - although neural networks models attempt to map non-linearities. For the multivariate case linear cross-correlation analysis helped establish the existence of a relationship between spot freight rate and FFA returns per route. Lagged terms that were most significant are primarily candidates for input variables.

5 FORECASTING PERFORMANCE RESULTS

All models, estimated over the initial estimation period, are used to generate one-step ahead out-of-sample forecasts. The forecasting performance of each model is presented in matrix form in tables F.5 and F.6 for spot rate forecasts and FFA rate forecasts, respectively. Forecasts made using first-differences will be transformed back to levels to ensure that the measures presented above are comparable for all models. The forecast performance of each model is assessed using the conventional root mean square error metric (RMSE) and Theil's U statistic. The latter allows a relative comparison of formal forecasting methods with a naïve model, a no-change random walk (RW1). In addition, we show the mean absolute percentage error (MAPE).

Table F.4: Estimation parameter and diagnostics[a]

Route	Contract	Measure	Univariate ARIMA	Univariate NN	Multivariate VAR	Multivariate VECM	Multivariate NN+
TD3	Spot	$\bar{R}^2$	0.9940	0.9944	0.9947	0.9948	0.9955
		RMSE	0.0420	0.0405	0.0397	0.0393	0.0366
		$Q(12)$	2.14	15.48	2.24	5.20	3.98
			(0.9992)	(0.2162)	(0.9989)	(0.9509)	(0.9837)
	FFA 1M	$\bar{R}^2$	0.9904	0.9908	0.9905	0.9907	0.9894
		RMSE	0.0463	0.0454	0.0460	0.0456	0.0486
		$Q(12)$	12.31	10.33	7.48	8.15	19.02
			(0.4211)	(0.5871)	(0.8241)	(0.7737)	(0.0880)
	FFA 2M	$\bar{R}^2$	0.9916	0.9913	0.9917	0.9920	0.9927
		RMSE	0.0400	0.0406	0.0397	0.0395	0.0373
		$Q(12)$	10.75	17.70	10.13	8.19	8.11
			(0.5501)	(0.1250)	(0.6049)	(0.7703)	(0.7768)
TD5	Spot	$\bar{R}^2$	0.9880	0.9887	0.9893	0.9899	0.9900
		RMSE	0.0489	0.0474	0.0464	0.0450	0.0447
		$Q(12)$	2.93	12.40	14.71	3.97	18.26
			(0.9960)	(0.4141)	(0.2577)	(0.9839)	(0.1081)
	FFA 1M	$\bar{R}^2$	0.9927	0.9931	0.9928	0.9930	0.9930
		RMSE	0.0335	0.0326	0.0334	0.0331	0.0329
		$Q(12)$	8.92	17.58	20.63	20.11	13.75
			(0.7095)	(0.1292)	(0.0561)	(0.0651)	(0.3171)
	FFA 2M	$\bar{R}^2$	0.9952	0.9957	0.9953	0.9955	0.9953
		RMSE	0.0260	0.0244	0.0257	0.0256	0.0255
		$Q(12)$	5.71	6.96	12.06	11.10	20.52
			(0.9298)	(0.8603)	(0.4406)	(0.5208)	(0.0579)

[a] Estimated coefficients of ARIMA and VAR estimated using daily data on spot and FFA freight rates over the period 5 April 2004 to 16 February 2010. All values are transformed back to levels. $Q(12)$ is the Ljung and Box Q-statistic testing up to 12th-order serial correlation in the residuals, and the figures in brackets show exact significance levels for the tests.

Table F.5: One-step ahead forecast performance for Route TD3[a]

			Univariate		Multivariate		
Contract	Measure	RW1	ARIMA	NN	VAR	VECM	NN+
Spot	$\bar{R}^2$	0.9659	0.9723	0.9748	0.9752	0.9756	0.9752
	MAPE	0.6769	0.6044	0.5938	0.5717	0.5541	0.5713
	RMSE	0.0468	0.0425	0.0406	0.0408	0.0397	0.0403
	Theil's U	1.0000	0.9087	0.8738	0.8726	0.8591	0.8710
FFA 1M	$\bar{R}^2$	0.9740	0.9764	0.9771	0.9761	0.9759	0.9769
	MAPE	0.5129	0.5084	0.5068	0.5151	0.5173	0.5176
	RMSE	0.0307	0.0293	0.0289	0.0295	0.0295	0.0291
	Theil's U	1.0000	0.9530	0.9406	0.9609	0.9614	0.9494
FFA 2M	$\bar{R}^2$	0.9577	0.9593	0.9595	0.9594	0.9590	0.9601
	MAPE	0.4968	0.5022	0.5026	0.5030	0.4991	0.5025
	RMSE	0.0284	0.0279	0.0277	0.0279	0.0279	0.0276
	Theil's U	1.0000	0.9826	0.9786	0.9839	0.9825	0.9744

[a] The table shows the number (282) of one-step ahead forecasts in the period 17 February 2010 to 1 April 2011.

Table F.6: One-step ahead forecast performance for Route TD5[a]

			Univariate		Multivariate		
Contract	Measure	RW1	ARIMA	NN	VAR	VECM	NN+
Spot	$\bar{R}^2$	0.9397	0.9475	0.9521	0.9578	0.9595	0.9564
	MAPE	0.7827	0.7373	0.7174	0.6656	0.6422	0.6764
	RMSE	0.0578	0.0540	0.0516	0.0485	0.0471	0.0496
	Theil's U	1.0000	0.9345	0.8996	0.8401	0.8185	0.8649
FFA 1M	$\bar{R}^2$	0.9595	0.9627	0.9625	0.9623	0.9621	0.9628
	MAPE	0.4832	0.4675	0.4663	0.4703	0.4672	0.4675
	RMSE	0.0298	0.0287	0.0287	0.0290	0.0288	0.0287
	Theil's U	1.0000	0.9622	0.9619	0.9701	0.9626	0.9612
FFA 2M	$\bar{R}^2$	0.9617	0.9616	0.9628	0.9637	0.9639	0.9623
	MAPE	0.3602	0.3698	0.3629	0.3559	0.3520	0.3617
	RMSE	0.0222	0.0223	0.0219	0.0216	0.0216	0.0220
	Theil's U	1.0000	1.0043	0.9873	0.9751	0.9725	0.9936

[a] see notes to table F.5.

All models outperform their naïve benchmark, except the ARIMA model in predicting the TD5 FFA 2M. Some regularities stand out from the two tables. First, the FFA rates are much harder to forecast than the spot rates. This phenomenon is not unusual for freight rates and confirms prior studies in the tanker market. Second, in most cases the multivariate models are superior against the univariate representives. We can find this advantage especially for spot freight rates. But this error difference or advantage declines in the FFA contracts. Furthermore, the VECM, which has an equilibrium correction feature, perform better than VAR models for forecasts of spot rates, but not for forecasts of FFA rates. The neural network results are comparable to those of the other models. It is interesting that the univariate NN achieve relatively good results, but the multivariate NN+ is not able to reinforce this advantage significantly. It seems, that the neural network as a non-linear approximator is already able to extract sufficient information out of the univariate time-series. The additional information contained in other time-series is therefore not needed.

6 FORECASTING PERFORMANCE EVALUATION BY ECONOMIC CRITERIA

Statistical performance measures are often inappropriate for financial applications. For example, Leitch and Tanner (1991) show a lack of significant correlation between profits and RMSE in forecasts of T-bill rates. Therefore, predicting the direction is a practical issue which usually affects a financial trader's decision to buy or sell a freight rate contract. Based on the generated results we provide a simple trading simulation to evaluate our forecasting performance in this section.

6.1 *Trading Strategy and Experiment*

The trading simulation assumes that, at the beginning of each trading day, the investor makes an asset allocation decision. Consider a freight rate contract whose prices fluctuate from day to day and the mid price on the tth day ($t = 0, 1, 2, \ldots, n$) is q_t. Let $p_t = \ln q_t$ be the log price and $r_t = p_t - p_{t-1}$ be the continuously compounded return on day t. We can generate trading signals now by the following rule:

$$\begin{cases} \text{long, if} & \hat{p}_{t+1} > p_t \\ \text{short, if} & \hat{p}_{t+1} < p_t \end{cases}$$

A long signal is to buy contracts at the current price, while a short signal is to sell contracts at the current price. This approach has been widely used in the literature; see, for example, Hsu et al. (1993). Therefore, we formulate a set of trading rules guided by the directions predicted by the mentioned forecasting models. Except for the straightforward naïve strategy, a random walk, all benchmark models were estimated on our in-sample period. The naïve strategy is defined by $\hat{r}_{t+1} = r_t$, where r_t is the actual rate of return at period t and $\hat{r}_{t+1}$ is the forecast rate of return for the next period. So, we switch from the no-change random walk to a constant (last) change random walk model (RW2).

The testing period runs from 17 February 2010 to 1 April 2011 for a total of 282 days of out-of-sample observations. In the trading experiment, it is assumed that during the initiation period, an investor will invest 1 money unit at the beginning of each contract period. So far, our results have been presented without accounting for transaction costs during the trading simulation.

6.2 *Results and Analysis*

The net gain in assets, number of trades executed, and the rate of return over the out-of-sample forecast horizon are shown in table F.7 and F.8 for TD3 and TD5. The initial investments are identical in all models due to the buy-and-hold strategy. Therefore, all measures are comparable. We see some implications: All models earn a positive trading result in case of no transaction costs. However, it is obvious, that the trading results in spot rates are more profitable than those for FFA contracts. This is also valid for the directional measures "winning trades per %". In most cases the models outperform the naïve RW2 model, except some time series models in predicting FFA prices. The multivariate NN+ undermatch the RW2 benchmark trading results for TD3 spot freight rates.

Additional observations are worth pointing out. The results generated by NN are encouraging in comparison to the other models. For every predicted asset the univariate NN shows the best performance across all models (univariate and multivariate) with respect to the important measures of net gain and risk-adjusted return as measured by the Sharpe ratio. ARIMA and VAR results show no unambiguous picture. Both models outperform the RW2 in case of spot rates. But ARIMA does not perform for TD5 FFA 2M contracts and VAR get worse results for TD3 FFA contracts. The multivariate VECM shows relatively good and stable results, except for the FFA 1M contracts. The multivariate NN+ achieves only in some cases preeminent trading results, e.g. for the TD5 spot freight rates. As mentioned above, additional time series do not improve the neural network performance. We conclude, that both VECM and univariate NN may generate more robust trading results for this time series and perform better than the other forecasting models.

7 CONCLUSIONS AND RECOMMENDATIONS

In this paper, we have examined the forecasting and trading performance of various standard linear time series models and a non-linear neural network to jointly predict spot and forward freight rates (FFA prices). We have focused on short-term forecasting, more precisely a one-step ahead forecasting horizon. To our knowledge there is a lack in the literature of joint predictions of freight rates and derivatives with neural networks and traditional time series models. We have built on prior

Table F.7: Trading performance for Route TD3[a]

Contract	Measure	RW2[b]	Univariate		Multivariate		
			ARIMA	NN	VAR	VECM	NN+
Spot	# trades	282	282	282	282	282	282
	net gain	4.76	5.52	6.07	5.72	5.48	4.64
	log-returns %	1.69	1.96	2.15	2.03	1.94	1.65
	Sharpe ratio	0.39	0.46	0.52	0.48	0.46	0.38
	max profit	0.17	0.33	0.33	0.33	0.33	0.17
	max loss	−0.33	−0.20	−0.08	−0.20	−0.20	−0.33
	winning trades %	0.73	0.73	0.71	0.73	0.72	0.71
	winning trades up %	0.68	0.79	0.71	0.71	0.71	0.69
	winning trades down %	0.77	0.69	0.71	0.75	0.74	0.73
FFA 1M	# trades	282	282	282	282	282	282
	net gain	2.01	2.12	2.35	1.79	1.81	2.05
	log-returns %	0.71	0.75	0.83	0.64	0.64	0.73
	Sharpe ratio	0.24	0.25	0.28	0.21	0.21	0.24
	max profit	0.14	0.14	0.14	0.14	0.14	0.14
	max loss	−0.07	−0.09	−0.07	−0.07	−0.09	−0.09
	winning trades %	0.55	0.57	0.58	0.56	0.58	0.59
	winning trades up %	0.52	0.55	0.51	0.55	0.64	0.54
	winning trades down %	0.59	0.59	0.63	0.58	0.53	0.62
FFA 2M	# trades	282	282	282	282	282	282
	net gain	1.01	1.12	1.23	0.61	1.14	1.72
	log-returns %	0.36	0.40	0.44	0.22	0.40	0.61
	Sharpe ratio	0.13	0.14	0.16	0.08	0.14	0.22
	max profit	0.10	0.10	0.10	0.10	0.10	0.10
	max loss	−0.08	−0.08	−0.08	−0.07	−0.08	−0.08
	winning trades %	0.51	0.54	0.53	0.50	0.57	0.54
	winning trades up %	0.52	0.54	0.50	0.54	0.62	0.52
	winning trades down %	0.51	0.53	0.56	0.46	0.51	0.56

[a] The table shows several trading performance measures in the period 17 February 2010 to 1 April 2011.

[b] RW2 is the last-change random walk, where the actual rate of return is the forecast of the next period.

Table F.8: Trading performance for Route TD5[a]

			Univariate		Multivariate		
Contract	Measure	RW2	ARIMA	NN	VAR	VECM	NN+
Spot	# trades	282	282	282	282	282	282
	net gain	5.73	6.45	6.95	7.13	7.15	7.32
	log-returns %	2.03	2.29	2.47	2.53	2.54	2.60
	Sharpe ratio	0.38	0.43	0.51	0.49	0.49	0.50
	max profit	0.23	0.40	0.40	0.40	0.40	0.40
	max loss	−0.40	−0.11	−0.11	−0.11	−0.11	−0.11
	winning trades %	0.73	0.74	0.74	0.73	0.72	0.74
	winning trades up %	0.71	0.80	0.73	0.72	0.72	0.75
	winning trades down %	0.76	0.69	0.74	0.74	0.72	0.73
FFA 1M	# trades	282	282	282	282	282	282
	net gain	2.01	2.12	2.35	1.81	1.81	2.24
	log-returns %	0.71	0.75	0.83	0.64	0.64	0.79
	Sharpe ratio	0.20	0.22	0.27	0.22	0.23	0.28
	max profit	0.14	0.11	0.11	0.11	0.11	0.11
	max loss	−0.07	−0.10	−0.08	−0.09	−0.09	−0.07
	winning trades %	0.55	0.59	0.62	0.59	0.59	0.60
	winning trades up %	0.52	0.57	0.61	0.58	0.60	0.71
	winning trades down %	0.59	0.61	0.62	0.59	0.58	0.49
FFA 2M	# trades	282	282	282	282	282	282
	net gain	1.01	0.58	1.28	1.40	1.52	1.08
	log-returns %	0.36	0.21	0.45	0.49	0.54	0.38
	Sharpe ratio	0.16	0.09	0.21	0.23	0.25	0.17
	max profit	0.10	0.10	0.10	0.10	0.10	0.10
	max loss	−0.08	−0.07	−0.07	−0.06	−0.06	−0.07
	winning trades %	0.51	0.52	0.56	0.57	0.59	0.56
	winning trades up %	0.52	0.47	0.57	0.53	0.60	0.60
	winning trades down %	0.51	0.56	0.55	0.60	0.59	0.53

[a] see notes to table F.7.

investigations, but we have extended our study to freight rate derivatives for the most liquid routes in the dirty tanker market TD3 and TD5 and use a wider range of time series forecasting models. In addition to conventional forecasting performance measures, we have evaluated our results in a simple trading simulation. This is achieved by the fact, that trading strategies guided by forecasts on the direction of price change may be more effective and generate higher profits than statistical performance measures.

We conclude, that neural networks are suitable for short-term forecasting and trading of tanker freight rates and derivatives. For the two liquid tanker routes we implicate that short-term forecasting with neural networks leads to better results than other traditional time series models. Our forecasting results confirm prior studies concerning time series models. If the derivatives market is liquid enough to include some information about future spot rates into the prices, we should observe cointegration between spot rates and FFA prices, and convergence of spot rates towards FFA prices, rather than vice versa. Spot freight rates and FFA prices are indeed cointegrated. But the models suggest that, contrary to our expectations, forward rates adjust more strongly than spot rates to close the gap between spot and forward rates. However, out-of-sample forecasting with multivariate forecasting models show that they are not helpful in predicting FFA prices, but do help predict spot freight rates. The results of neural networks are in line with these findings. In our evidence, both VECM and univariate neural networks may generate more robust trading results for the analyzed time series than the other forecasting models.

For maritime actors like shipowners and charterers our findings are encouraging in the sense that they suggest that spot freight rates and FFA prices are forecastable. In addition, the rates offered by FFA help anticipate spot freight rates. For trading purposes neural networks and time series models like VECM could be a starting point for building a decision support model for spot freight rate and FFA trading. Several extensions for further research are also thinkable. On the one hand, it would be interesting to examine longer investment horizons. On the other hand, we do not include further exogenous input variables in multivariate models like crude oil prices, maritime data, which represents the demand and supply of freight rates or any other variables. Maybe, this inclusion could improve forecasting and/or trading results. Furthermore, this investigation may be also extended to other financial freight rate products. Freight rate option prices in the tanker market are actually rarely analyzed. The challenge is that these financial products are not very liquid. Empirical data is still scarce.

G

THE »TRADING TANKER FREIGHT RATES« PAPER

Short-Term Trading Performance of Spot Freight Rates and Derivatives in the Tanker Shipping Market: Do Neural Networks provide suitable results?

Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2012). *Short-Term Trading Performance of Spot Freight Rates and Derivatives in the Tanker Shipping Market: Do Neural Networks provide suitable results?* In: Engineering Applications of Neural Networks, 13th International Conference, EANN 2012, London, UK, September 20-23, 2012. Communications in Computer and Information Science Volume 311, pp. 443-452.

ABSTRACT

In this paper we investigate the forecasting and trading performance of linear and non-linear methods, in order to generate short-term forecasts in the dirty tanker shipping market. We attempt to uncover the benefits of using several time series models and the potential of neural networks. Maritime forecasting studies using neural networks are rare and only focus on spot rates. We build on this kind of investigation, but we extend our study on freight rates derivatives or Forward Freight Agreements (FFA) in a simple trading simulation. Our conclusion is, that non-linear methods like neural networks are suitable for short-term forecasting and trading freight rates, as their results match or improve on those of other models. Nevertheless, we think that further research with freight rates and corresponding derivatives is developable for decision and trading applications with enhanced forecasting models.

KEYWORDS

Shipping Freight Market, Neural Network, Forecasting Performance, Trading Performance

DOI 10.1007/978-3-642-32909-8_45

JEL C45, C53, G13, G14, G17

H

THE »FORECASTING FREIGHT RATES II« PAPER

Spot and freight rate futures in the tanker shipping market: short-term forecasting with linear and non-linear methods

Spreckelsen, C.v. , Mettenheim, H.-J.v. and Breitner, M.H. (2012). *Spot and freight rate futures in the tanker shipping market: short-term forecasting with linear and non-linear methods.* In: Operations Research Proceedings 2012: Selected Papers of the International Annual Conference of the German Operations Research Society (GOR), Leibniz University of Hannover, Germany, September 5-7, 2012, pp. 247-252.

ABSTRACT

This paper tests the forecasting and trading performance of popular linear and non-linear forecasting models in predicting spot and forward freight rates in the dirty tanker shipping market. Maritime forecasting studies using neural networks are rare and only focus on spot rates. We build on former investigations, but we extend our study on freight rates derivatives. Our conclusion is, that non-linear methods like neural networks are suitable for short-term forecasting and trading freight rates, as their results match or improve on those of other models.

KEYWORDS

Option Pricing, Delta-hedging, Neural Networks, High-Frequency Data

DOI 10.1007/978-3-319-00795-3_36

JEL C45, C53, G13, G14, G17

J THE »NOMADIC COMPUTING« PAPER

Geschäftsprozessorientierte Analyse und Bewertung der Potentiale des Nomadic Computing

Spreckelsen, C.v. , Bartels, P. and Breitner, M.H. (2006). *Geschäftsprozessorientierte Analyse und Bewertung der Potentiale des Nomadic Computing.* IWI Discussion Paper No. 17, 14. Dezember 2006.

ABSTRACT

Nomadic Computing stellt ein neues Paradigma der Computernutzung dar, in welchem der Nutzer von überall und zu jeder Zeit auf Daten, Informationen und Services zu-greifen kann. Über diese Vision hinaus stellt sich die Frage der betriebswirtschaftlichen Analyse und Bewertung dieser Technologie. Die Analyse und Bewertung von Nutzenpotentialen des Nomadic Computing ist insbesondere aus dem Grund erforderlich, da eine Einführung neuer Technologien oft technikgetrieben und nicht nachfragegetrieben erfolgt. Interessante Business Cases werden insbesondere im betrieblichen Wertschöpfungsprozess gesehen. Eine Einführung von Nomadic Computing bedeutet zum Teil gravierende Auswirkungen auf die Struktur der Unternehmensprozesse und ist daher einer betriebswirtschaftlichen Analyse zu unterziehen.

KEYWORDS

Nomadic Computing, Mobile Systeme, Prozessoptimierung, Potentialbewertung

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JEL L63, M15, O32, O33

Geschäftsprozessorientierte Analyse und Bewertung der Potentiale des Nomadic Computing

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1 EINLEITUNG

> *„But, in fact, most of us are nomads, moving between office, home, airplane, hotel, automobile, branch office, conference room, bedroom, etc. In so doing, we often find ourselves decoupled from our 'home base' computing and communications environment.“*
>
> Leonard Kleinrock 1997

Klassische Nomaden bewegen sich seit Beginn der Menschheitsgeschichte in ihrem Wanderungsgebiet und ziehen dabei von Ort zu Ort, wo sie sich jeweils an neue Umgebungsbedingungen anpassen. Sie bringen ihre Ausrüstung zum Teil mit; zum Teil finden sie Informationsmedien - z. B. Sonnenstand - zur Bewältigung der aktuellen Aufgaben und Orientierungsfindung auch vor.[1] In der ökonomischen Realität bestimmt seitdem Mobilität zunehmend Arbeitsabläufe und Prozesse. Unterwegs benutzen die modernen Nomaden smarte Geräte wie Notebook, PDA und Mobiltelefone; am Zielpunkt finden sich stationäre Geräte, an denen sie ihre Aktivitäten fortsetzen können.

Ausgehend von dieser Tatsache erwächst die Vision, die benötigten Informationen zu jeder Zeit, an jedem Ort, mit jedem möglichen Medium zur Verfügung gestellt bekommen. Dies ist das Paradigma des Nomadic Computing: der moderne Nomade kann kontinuierlich seine Aufgaben - ob unterwegs oder am Zielort angekommen - wahrnehmen. Die mobilen und stationären Endgeräte erkennen, speichern und passen die Profile des Nomaden und seiner Umgebungen an, um ihn bei seinen privaten oder geschäftlichen Tätigkeiten zu unterstützen. Hinter der Vision des Nomadic Computing deutet sich bereits die Motivation für einen kommerziellen Einsatz unter betriebswirtschaftlichen Gesichtspunkten an. Angeregt wird diese These durch die Frage, ob Nomadic Computing Nutzenpotentiale für alle Wirtschaftsakteure ermöglicht. Die geschäftsprozessorientierte Analyse und Bewertung von Potentialen des Nomadic Computing ist Gegenstand dieses Diskussionspapieres.

[1] Vgl. Oppermann (2003)

2 KONZEPTUELLE AUSGESTALTUNG DES NOMADIC COMPUTING

2.1 *Nomadic Computing als neues Paradigma*

Leonard Kleinrock hat 1995 mit dem Aufkommen des Nomadic Computing einen Paradigmenwechsel im Gegensatz zum herkömmlichen Computereinsatz angekündigt.[2] „Anytime-anywhere" - lauten die neuen Schlagworte, die mit dem Zugang zu Informationen in Verbindung gebracht werden. Dieser Zugang soll unabhängig sein vom Aufenthaltsort, vom verwendeten Gerät und der Betriebsplattform, der Art des Netzzugriffs und der Bandbreite, und davon, ob der Benutzer sich an einem Ort aufhält oder sich in Bewegung befindet. Unabhängigkeit bedeutet, dass die Computer-Umgebung von den Applikationen wahrgenommen wird und sich diese automatisch an die neuen Prozesse, Kommunikationsfähigkeiten und Zugangsmöglichkeiten anpassen können. Entsprechend der Anforderungen nach Mobilität müssen Kommunikationssysteme, über welche dem Benutzer mobile Anwendungen angeboten werden, Basisfunktionalitäten einer transparenten Unterstützung der Mobilität zur Verfügung stellen. In Referenzmodellen werden verschiedene primäre Mobilitätsformen unterschieden.[3]

Die Begriffsbestimmung des Nomadic Computing selbst lässt sich in der Literatur nicht eindeutig eingrenzen. Namensgebend für das Nomadic Computing ist die Entwicklung ganzer Gesellschaftsschichten zu modernen Nomaden. Eine genaue Umschreibung ist auch von den verwandten Paradigmen, wie z. B. dem Ubiquitous Computing, abhängig.[4] So trägt Nomadic Computing Züge des Ubiquitous Computing, betont aber den Menschen als soziales Wesen, der von überall, auch beim Umherziehen außerhalb des festen Büros, Zugriff auf Daten und Dienste haben möchte.[5] *„Dies ist das Wesen nomadischer Informationssysteme: die Durchgängigkeit der Verfügbarkeit von Informations- und Kommunikationsdiensten über die ganze Prozesskette mobiler Aktivitäten und die Einbettung der Dienste in den Kontext der Nutzung."*[6] Weitere Begriffsbestimmungen zeigt Tabelle J.1.

Die Bereitstellung von Kommunikationszugängen erfolgt mit einer durchgängig personalisierten Sicht auf diese Dienste. Im Sinne der drei Mobilitätsformen erhält der Nutzer zu jeder Zeit Zugriff auf die Informationen und Dienste, die er vor Ort antrifft. Damit kann eine Definition des Nomadic Computing festgelegt werden.

Definition. Nomadic Computing beschreibt die aus der Sichtweise des Benutzers kontinuierliche Bereitstellung von Informations- und Kommunikationszugängen durch eine unabhängige Nutzung eines Engerätes (portabel/stationär), durch eine

[2] Vgl. Kleinrock (2001).
[3] Vgl. Hess, T. et al. (2005); vgl. auch Roth (2002). Hess et al. stellen zusätzlich eine vierte Form, die Sitzungsmobilität, vor. Daneben unterscheidet man sekundäre Mobilitätsformen, die systematische und administrative Aspekte der primären Mobilitätsformen abdecken.
[4] Vgl. Mattern (2003); Müller-Schloer (2001).
[5] Vgl. Kleinrock (2001); vgl. Kleinrock (1995).
[6] Fraunhofer-Institut für Angewandte Informationstechnik FIT (2005a).

Tabelle J.1: Begriffsbestimmungen Nomadic Computing

Autor	Definition
La Porta et al. (1996)	„Following the explosive growth of cellular telecommunication and paging services, there is an increased interest in anywhere, anytime computing. Often called nomadic computing, the goal is to provide users with access to popular desktop applications, applications specially suited for mobile users, and basic communication services in a mobile, sometimes wireless, environment.“
Kleinrock (1996)	„Nomadicity may be defined as the system support needed to provide a rich set of computing and communication capabilities and services to nomads as they move from place to place in a transparent, integrated and convenient form. ... Nomadic Computing means that wherever and whenever we move around, the underlying system always knows who we are, where we are, and what services we need.“
Lyytinen and Yoo (2002)	„A nomadic information environment is a heterogeneous assemblage of interconnected technological and organizational elements, which enables physical and social mobility of computing and communication services between organizational actors both within and across organizational borders.“
Nakamura (2001)	„Such a nomadic environment is one where you don't need to carry various devices with you. Rather, the places you go such as companies, schools, homes, business trip destinations, hotels and rental offices are all equiped with information devices available for your use. This means creating an environment where users can access the same data regardless of their location, and where applications such as screen-based desktop environments can be used just like at one's home or office.“
Bagrodia et al. (2003)	„A nomadic computing application is a program that allows the user to leverage network connectivity, provided by a wired or wireless infrastructure, to access an utilise his data productively from any location, on any platform, and at any time.“
Oppermann (2003)	„Die Eigenart nomadischer Systeme liegt in der kontinuierlichen Bereitstellung von Informations- und Kommunikationszugängen über verschiedene Arten von Endgeräten, in verschiedenen Umgebungen mit einer durchgängig personalisierten Sicht auf diese Dienste.“
Fraunhofer-Institut für Angewandte Informationstechnik FIT (2005a)	„Nomadic Computing reflects the current context of usage defined by the location of the user, task or interests of the user and knowledge of the user. Nomadic Computing does not mean to increase mobility as a value per se but to support occuring mobility driven by tasks or interests of people.“

unabhängige Netzanbindung und durch einen räumlich ungebundenen Standort des Benutzers.

Damit grenzt sich Nomadic Computing von anderen Paradigmen durch eine stark benutzerorientierte Sichtweise ab. Die nomadischen Systeme erkennen den Nutzenkontext des Benutzers und passen die bereitgestellten Informationen und Dienste an das Profil und der Umgebung des Benutzers an.

2.2 *Wissenschaftliche Pilotprojekte im Nomadic Computing*

Die Vision des Nomadic Computing ist in der Wissenschaft bereits ausführlich diskutiert und an Pilotprojekten in der Realwelt erprobt worden. Grundsätzlich sind eine Vielzahl von potentiellen Anwendungsszenarien für einen konventionellen Einsatz denkbar, welche die Vision des Nomadic Computing in den Consumer-Bereich tragen könnten. Raumbezogene Handlungssituationen in öffentlichen Räumen wie Messen, Museen, Flughäfen, Einkaufs- und Erlebniswelten, Verwaltungs- und Dienstleistungskomplexen kommen als Anwendungsdomänen in Betracht. Bedeutende realisierte Pilotprojekte sind:

- Mit SAiMotion wurde ein Messeführer entwickelt,
- CoolTown[7] beschreibt - ähnlich dem Messeführer - ein Museumsführer und
- das Projekt CRUMPET verkörpert ein Tourismusinformationssystem.

Alle drei Anwendungsszenarien bilden eine dynamische Umgebung für den Einsatz kontextsensitiver Informationssysteme, die nützliche Anhaltspunkte für eine betriebswirtschaftliche Nutzenanalyse liefern können. SAiMotion und CRUMPET sollen in diesem Artikel kurz vorgestellt werden.

SAiMotion(Situation Awareness in Motion)

SAiMotion[8] entwickelt und evaluiert ein nomadisches Informationssystem, das den mobilen Besucher in einer komplexen Umgebung personalisierte und situativ angepasste Informationen bereitstellt.[9] Das Szenario beschreibt einen Messebesuch, der sowohl durch eine Messevorbereitung als auch durch eine Nachbereitung der Messe begleitet wird. Die Hauptaufgaben des Systems stellen die Navigation auf dem Messegelände und die Nutzung personalisierter Gelände- und Hallenpläne zur räumlichen und inhaltlichen Orientierung sowie zur Planung des Messebesuchs dar. Ergänzt werden diese Funktionen um ein Konfliktmanagement bei Änderungen von Terminen oder Verlegung von Veranstaltungsorten. Ziel ist es,

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[7] Vgl. Roth (2002); Kindberg and Barton (2001); Kindberg, T. et al. (2002).

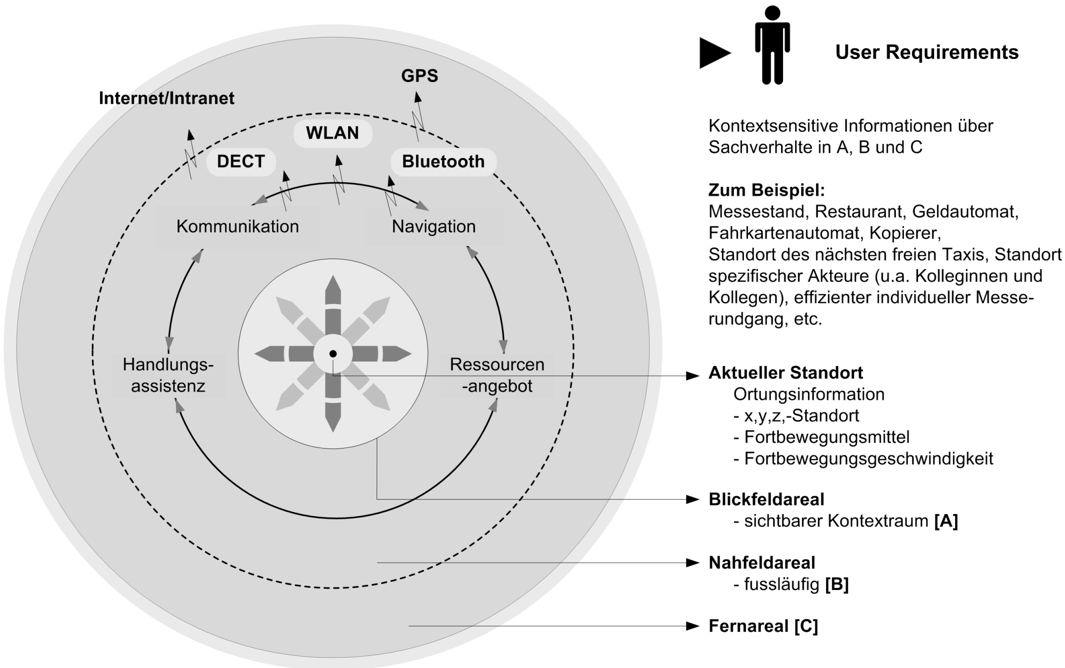
[8] Das Projekt SAiMotion wurde vom Bundesministerium für Forschung und Bildung im Rahmen des Programms „Leben und Arbeiten in einer vernetzten Welt“ gefördert; die Laufzeit des Projekts lief vom April 2001 bis Dezember 2003.

[9] Vgl. Bieber et al. (2002); Heidmann and Hermann (2003).

den Benutzer in seinem Informations-, Zeitmanagement- und Navigationsaufgaben zu unterstützen. Dazu wertet das System neben Ortsmerkmalen auch Benutzer-, Aufgaben- und Umgebungsmerkmale der aktuellen Situation aus und leitet daraus proaktiv geeignete Informations- und Diensteangebote ab.

Die Basis für die Akzeptanz von Informations- und Kommunikations-Systemen ist eine vereinfachte Informationsdarbietung, die auf die Situation, die Aufgabe und den Nutzer angepasst ist. In SAiMotion wird versucht, ein erschöpfendes Situations-Modell zu identifizieren und alle relevanten situativen Parameter für eine proaktive Informations-Darbietung und Interaktion zu nutzen. Die Abbildung J.1 zeigt vor diesem Hintergrund ein abstraktes Raummodell für kontextsensitive Interaktion und Kommunikation. Der SAiMotion-Ansatz konzentriert sich hierbei auf Interaktion und Kommunikation im Blick- und Nahfeldareal des Benutzers: Die Aufgabe sich in immer kürzeren Zyklen in neuen Raumumgebungen erfolgreich zu orientieren und spezifische Problemsituationen zielorientiert zu lösen, soll vom SAiMotion-System gezielt unterstützt werden. Dazu zählt die Modellierung der Aufgaben und Benutzerprofile sowie deren ablaufbegleitende Unterstützung.

Abbildung J.1: Raummodell kontextsensitiver Interaktion und Kommunikation



Die Benutzermodellierung in SAiMotion versucht ihrerseits, aus der Menge aller relevanten Informationen diejenigen herauszufiltern, die für den jeweiligen Benutzer relevant sind. Dieses Modell wird in Zusammenarbeit mit dem Benutzer und dem System verwaltet. Das System beobachtet den Benutzer, schließt daraus auf seine Interessen und kann auf Basis seiner Beobachtungen dem Benutzer vorschlagen, sein Interessensprofil zu ändern. Dadurch kann auf Interessensverschiebungen reagiert werden. Neben der Filterung von relevanten Informationen kann die Interessensmodellierung auch zur Priorisierung der gefilterten, relevanten Informationen genutzt werden.[10]

CRUMPET (Creation of user-friendly Mobile Personalised for Tourism)

Das EU-Projekt CRUMPET[11] hatte als wesentliches Ziel, Tourismus Services mit Mehrwert, die den nomadischen Benutzern über mobile und feste Netze bereitgestellt werden, zu implementieren und zu evaluieren.[12] CRUMPET versucht pragmatische und indivudualisierte Informationen über das Bestimmungsortgebiet, einschließlich deren Geschichte, Kultur, Klima und Natur zu berücksichtigen und stellt Informationen und Dienstleistungen für eine weit heterogenere touristische Bevölkerung ur Verfügung.

Das CRUMPET-System ist zunächst ein interaktiver Stadtplan im Handy-Format. Ein Tourist bewegt sich mit einem Handy-ähnlichen Gerät durch die fremde Stadt. Auf dem Display erkennt er seinen Standort, ruft Informationen in Schrift und Bild über die umliegenden Sehenswürdigkeiten ab und lässt sich auf dem digitalen Stadtplan den Weg dorthin zeigen. Wesentliche Eigenschaften des Systems stellen die Lokalisierung der Benutzer via GPS oder GSM, ein adaptives Benutzermodell, personalisierte und ortsabhängige Auswahl von Tourismusinformationen sowie die Anpassung der Informationsausgabe an die Endgeräte dar. CRUMPET betont daher insbesondere die Aspekte der Personifizierung von Dienstleistungen, die gegenwärtige Position des Benutzers und die persönlichen Interessen eines Benutzers.

Elektronische Dienste wie z. B. digitale Tourenplaner oder Restaurantführer existieren schon heute, sind aber nicht miteinander verknüpft. Beschränkungen liegen in der individuellen Extrahierung von Informationen und der durchgängigen Verfügbarkeit. CRUMPET kann eine Fülle unterschiedlicher Dienste integrieren und einem leistungsfähigen Funknetz zur Verfügung stellen. Das System zielt darauf ab, eine Dienstleistungsumgebung zu entwickeln, die generisch das traditionelle Internet und die drahtlosen Dienstleistungen integriert.

2.3 *Aktuelle Fragestellungen*

Für diese Pilotprojekte werden sodann große Chancen für den zukünftigen kommerziellen Massenmarkt prognostiziert, wenn sich der Einsatz von Anwendungen des Nomadic Computing aus betriebswirtschaftlicher Sicht rentiert. Grundsätzlich zeichnet sich die gegenwärtige Entwicklung und Bereitstellung mobiler Anwendungen und Dienste zeichnet sich dadurch aus, dass nach dem „Trial and Error"-Prinzip

[10] Zur technischen Unterstützung vgl. Fraunhofer-Institut für Angewandte Informationstechnik FIT (2005b).

[11] Das Projekt CRUMPET wurde durch das europäische Programm „Information Societies Technology" gefördert. Es startete am 1. Oktober 2000 und wurde im November 2002 mit Trials von Prototypen in Heidelberg, Helsinki, Aveiro und London erfolgreich beendet.

[12] Vgl. Specht and Oppermann (1999).

versucht wird, Killerapplikationen zu entwickeln. Es wird jeder denkbare neuartige mobile Dienst umgesetzt, ohne dass eine systematische Analyse der Potentiale durchgeführt wird. Dabei ist zu beobachten, dass bereits vorhandene mobile Dienste wie Navigationshilfen nicht oder äußerst langsam vom Markt aufgenommen werden. Im Widerspruch führen die kürzeren Innovationszyklen zu einer technologiebetriebenen Entwicklung, die einerseits eine systematische Spezifikation eines mobilen Dienstes erschwert und andererseits der systematischen Vorgehensweise bei der Potentialanalyse eine immer wichtigere Bedeutung zukommen lässt.[13]

Für den Bereich der Planung und Umsetzung mobiler Anwendungen existieren nur wenige Ansätze, die sich mit der Nutzenbewertung durch Prozessoptimierung beschäftigen. Hanhart et al. bemängeln, dass über die Prozessoptimierung hinaus weitergehende Nutzen- und Wirtschaftlichkeitsanalysen fehlen.[14] Sie führen daher eine kennzahlenbasierte Untersuchung durch. Behr führt eine Nutzen- und Kostenschäftzung für die Einführung eines Geo-Informationssystems auf, in der er verschiedene Nutzenkategorien bildet.[15]

Das erklärte Ziel der vorliegenden Arbeit ist es, identifizierte Nutzenpotentiale des Nomadic Computing zu analysieren und zu bewerten. Mit dem Ergebnis soll die Frage beantwortet werden, ob Nomadic Computing entscheidende Mehrwerte aus technischer und betriebswirtschaftlicher Sichtweise generieren kann. Der Ausgangspunkt der Untersuchung besteht in der Suche nach Erfolgsfaktoren und Treibern dieser neuen Technologie, die einen kommerziellen Einsatz im Massenmarkt erst begründen. Darauf aufbauend soll sich die Betrachtung von Nutzenpotentialen des Nomadic Computing schwerpunktmäßig auf den Einsatz in betrieblichen Prozessen konzentrieren.

3 PROZESSOPTIMIERUNG IN DER WERTSCHÖPFUNGSKETTE

Die mobile Präsenz und Prozessunterstützung einer Unternehmung ist keine Zukunftsvision mehr, sondern für viele Unternehmen aus den unterschiedlichsten Gründen - seien es Wettbewerbsgründe, geographische Aspekte oder andere Gründe - unverzichtbar. Erhebliche Rationalisierungschancen bieten häufig mobile Verfahren und Technologien zur Steuerung und Unterstützung von Geschäftsprozessen. Zur Identifikation dieser Potentiale rücken neben technologischen Fragen folgende Herausforderungen:[16]

- Welche Geschäftsprozesse können mobil unterstützt werden und wie sollen die Prozesse und Tätigkeiten nach der Mobilisierung gestaltet sein?
- Welche Steuerungs- und Rationalisierungseffekte können durch die mobile Unterstützung tatsächlich erzielt werden?

[13] Vgl. Amberg et al. (2004).
[14] Vgl. Hanhart et al. (2005).
[15] Vgl. Behr (2000).
[16] Vgl. Krcmar (2003).

- Wie kann Nomadic Computing dazu beitragen, dass eine Unternehmung am Markt erfolgreicher agiert und Wettbewerbsvorteile erlangt?

Im betrieblichen Einsatzfeld hingegen steht die Frage nach quantifizierbaren Optimierungspotentialen von Geschäftsprozessen und dem damit verbundenen Return-on-Invest- ment im Mittelpunkt des Interesses.[17] Für den kommerziellen Einsatz des Nomadic Computing sind daher betriebswirtschaftliche Kalküle anzustellen.

3.1 *Kritische Erfolgsfaktoren für die Kommerzialisierung*

Im Rahmen der Leistungserstellung kann Mobilität zur Unterstützung und Optimierung der innerbetrieblichen und unternehmensübergreifenden Wertschöpfung dienen. Ihre Nutzenpotenziale liegen insbesondere in den Möglichkeiten der nahtlosen unternehmensübergreifenden Integration aller am Geschäftsprozess beteiligten Partner, insbesondere wenn diese Prozesse verteilt ablaufen.

Dazu sind zunächst die betriebswirtschaftlichen Treiber bzw. erfolgskritische Faktoren herauszuarbeiten, die einen erfolgreichen Einsatz des Nomadic Computing grundsätzlich begründen. Dies soll nicht nur eine widerspruchsfreie Einbettung eines nomadischen Systems in die strategischen wie auch operativen Ziele gewährleisten, sondern auch fundamental abgesicherte Investitionsentscheidungen ermöglichen.

Lyytinen und Yoo gehen in ihrer Untersuchung nomadischer Umgebungen von drei grundlegenden Treibern aus. Die wesentlichen Neuerungen einer nomadischen Umgebung bestehen aus:[18]

- einem hohen Grad an Mobilität,
- dem konsequent hohen Grad an Skalierbarkeit von Diensten und Infrastrukturen sowie
- der Vielseitigkeit von Diensten bei der Datenbearbeitung und -übertragung - auch als Digitale Konvergenz bezeichnet.

Diese drei technologischen Treiber unterstreichen die hauptsächliche Entwicklung der zukünftigen Computertechnologie. Wenn alle drei Treiber ausnahmslos zusammentreffen, agieren sie als sich wechselseitig beeinflussende Treiber, welche die Entwicklung zukünftiger Computerumgebungen ausformen. Sie unterscheiden sich dann auch von dem ursprünglichen Mobile Computing und Pervasive Computing, die eine hohe Skalierbarkeit und Integration von Diensten sowie Infrastrukturen eher vernachlässigen.

Aus dem grundsätzlichen Wunsch nach Mobilität erwachsen weitere Bedürfnisse des Nutzers, die über die Beziehungen der drei Treiber hinausgehen - diese können

[17] Vgl. Rannenberg et al. (2005).
[18] Vgl. Lyytinen and Yoo (2002).

als weitere Erfolgsfaktoren einen erfolgreichen Einsatz des Nomadic Computing erklären. Die Grundbedürfnisse des Individuums können durch mobile Kommunikation effizienter und besser befriedigt werden. Zu diesen Grundbedürfnissen zählen:[19]

- *Durchgängigkeit von Prozessen:* Im Gegensatz zu heutigen Informationssystemen besteht der Wunsch nach einer kontinuierlichen Ausführbarkeit von Prozessen; und war unabhängig vom verwendeten Gerät und Anwendung.
- *Ubiquität:* Betriebliche Informationssysteme sind innerhalb einer Unternehmung schon heute fast allgegenwärtig. Keine Maschine, kein Arbeitsplatz, der nicht mit einem Computer ausgestattet ist, um auf alle oder an diesem Ort besonders benötigte Informationen zugreifen zu können.
- *Personalisierung*: Der moderne Nomade sehnt sich bei seinen Wanderungen nach einer intensiven Unterstützung seiner mobilen Systeme. Zugeschnitten auf seine Persönlichkeit, erfährt er an unbekannten Orten oder Situationen eine für ihn passende Hilfe.
- *Kontextsensivität*: Kontextsensivität bedeutet, dass Umfeld eines Benutzers zu erfassen und auszuwerten, um die für den Benutzer relevanten Dienste einzugrenzen und aktiv anzubieten.
- *Erreichbarkeit*: Mobile Nutzer können nicht nur Informationen weltweit und von jedem Ort aus abrufen, sie sind selbst prinzipiell zu jeder Zeit und an jedem Ort erreichbar.

Vor dem Hintergrund der erfolgskritischen Faktoren des Nomadic Computing sind die Anbieter von Kommunikationsdienstleistungen daran interessiert, diese in Nutzenpotentiale für alle Marktteilnehmer umzumünzen.[20] Der in dieser Arbeit herangezogene Compass-Ansatz (Cooperation Model for Personalized And Situation dependent Services) stellt ein methodengestüztes Verfahren für die kooperative Bereitstellung situationsabhängiger mobiler Dienste dar - lässt sich also auch auf das Nomadic Computing übertragen.[21]

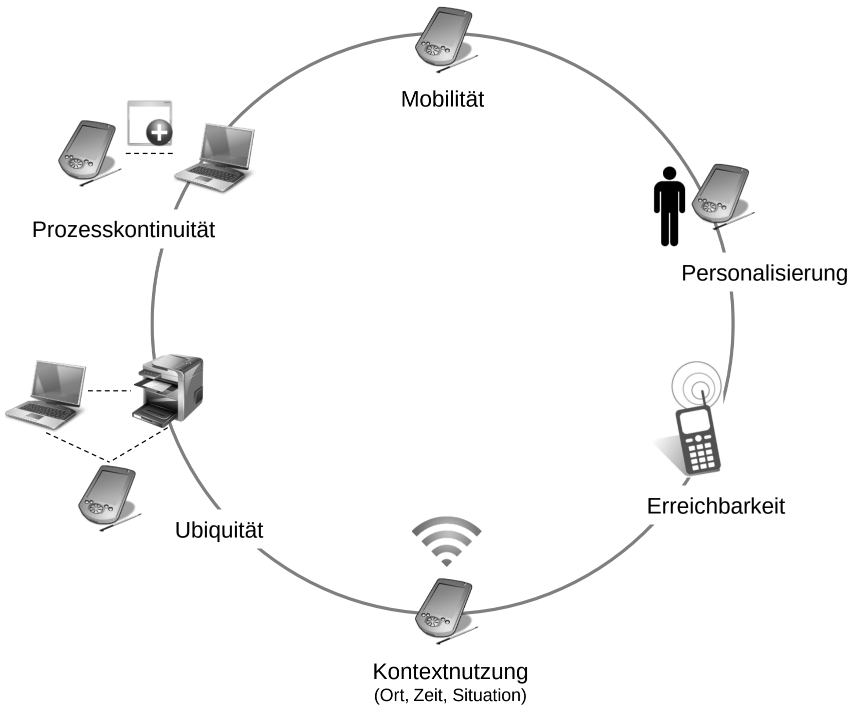
Voraussetzung für eine optimale Ausschöpfung der Potentiale stellen in mobil verteilten Systemen zum einen ein Situationskonzept, zum anderen ein Nutzungszyklus dar. Das Situationskonzept systematisiert den mobilen Nutzungskontext und macht die Nutzungssituation für die kooperative Leistungserstellung anwendbar. Der Erfolg eines Dienstes und die Akzeptanz der Kunden sind maßgeblich davon abhängig, wie der Situationsbegriff systematisiert und konkretisiert wird.

[19] Vgl. Fleisch et al. (2003).

[20] Vgl. Scheer, A.-W. et al. (2001). In einem Interaktionsmodell können generell die zugrundeliegenden Leistungs- und Informationsbeziehungen zwischen den beteiligten Marktteilnehmern aufgezeigt werden. Vgl. dazu auch Camponovo and Pigneur (2002) und Pigneur (2002).

[21] Vgl. Amberg et al. (2002); Amberg et al. (2003); Amberg et al. (2004).

Abbildung J.2: Bedürfnisse als Treiber im Nomadic Computing



Der Nutzungszyklus stellt den Prozessablauf für die Bereitstellung situationsabhängiger mobiler Dienste dar und geht auf unterschiedliche Arten von Diensten ein:

- Individualisierte Dienste sind benutzer-initiierte Dienste, die an seine speziellen Bedürfnisse angepasst werden.
- Proaktive Dienste sind automatisch erzeugte Dienste, die durch das Eintreten von Ereignissen initiiert werden.
- Evolutionäre Dienste sind durch Auswertung und Evaluierung sukzessiv verbesserte Dienste.

Durch dieses Spektrum an situationsabhängigen mobilen Diensten wird ein Dienstanbieter in die Lage versetzt, in umfassender Art und Weise seine Dienste an die Bedürfnisse der mobilen Kunden anzupassen.

3.2 *Typische Prozessstrukturen für mobile IT-Unternehmungen*

Die erfolgskritischen Faktoren bzw. Treiber des Nomadic Computing machen eine Anwendung in geschäftsprozessorientierten Unternehmungen zur Unterstützung betrieblicher Arbeitsprozesse attraktiv. Um attraktive Nutzenpotentiale zu adressieren und damit betriebswirtschaftlichen Nutzen zu generieren, bedarf es eine

Konzentration auf eine Effizienz- bzw. Effektivitätssteigerung, die das Resultat erfolgreicher Anwendung von Nomadic Computing-Technologien ist und damit strategische Ziele im Prozessmanagement verkörpern. Mit Effektivität wird das Streben nach Produktivität bezeichnet, Effizienz bezeichnet die Wirtschaftlichkeit als Verhältnis zwischen einer Kostensituation bezüglich einer Bezugsgröße wie Leistungssituation oder günstigste Kostensituation.[22] Es können drei wesentliche Beurteilungskriterien zur Bewertung von Prozessen identifiziert werden:[23]

- Qualität: Es ist zu messen, inwieweit das Prozessergebnis einer bestimmten Zielvorstellung entspricht.
- Zeit (Durchlaufzeit): Zur Beurteilung der Zeiten werden häufig nicht nur Durchschnittswerte, sondern auch Bandbreiten der zeitlichen Schwankungen durch die Erfassung von minimalen bzw. maximalen Zeiten berücksichtigt.
- Kosten: Ermittlung der Einzelkosten der einzelnen Prozesselemente (Bearbeitungs-, Transport-, Kommunikationskosten).

Ferner kann mit Innovation ein viertes Kriterium ergänzt werden, das die generelle Fähigkeit von Prozessen beschreibt, sich ständig weiterzuentwickeln und neue Entwicklungen zu integrieren.

Die Herausforderung liegt hierbei in der Identifikation dieser Nutzenpotentiale.[24] Durch nomadische Technologien können interne Prozesse effizienter und schneller gesteuert werden. Für den Einsatz des Nomadic Computing ist es daher elementar wichtig, Mobilität in Geschäftsprozessen zu identifizieren. Hierzu müssen zunächst klassische Geschäftsprozesse abgegrenzt werden.[25]

In verteilten Prozessstrukturen weisen Prozesse selten Züge von Routine-Prozessen auf; Bearbeitungsregeln sind in mobilen Prozessen kaum im voraus definiert, sondern ändern sich in solch einem Ad-hoc-Geschäftsprozess dynamisch und werden z. T. neu erzeugt. Diese Erkenntnis führt zu einer speziellen Begriffsbestimmung mobiler Geschäftsprozesse - im Folgendem auch als nomadischer (Geschäfts-)Prozess bezeichnet - in verteilten Strukturen. Köhler und Gruhn haben bereits Charakteristika mobiler Geschäftsprozesse festgelegt, nach dem sich im Ursprung ein mobiler Geschäftsprozess derart definiert, dass insbesondere die Unsicherheit des Ortes herausgestellt wird. Diese Abgrenzung soll als Grundlage für die Entwicklung eines nomadischen Geschäftsprozess dienen.

Definition. Ein nomadischer Geschäftsprozess beschreibt einen für den Einsatz für Nomadic Computing potentiell geeigneten Geschäftsprozess, der im Mittelpunkt den ausführenden Menschen sieht und durch folgende Einschränkungen eingegrenzt wird:

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[22] Vgl. Heinrich (2002).
[23] Vgl. Krcmar (2003).
[24] Vgl. Fleisch et al. (2003).
[25] Vgl. zur Definition von Geschäftsprozessen Stahlknecht and Hasenkamp (2001); vgl. auch Scheer, A.-W. et al. (2001) sowie Hansen and Neumann (2001).

1. *Es liegt eine Unsicherheit des Ausführungsortes und der -zeit vor,*
2. *diese Einschränkungen sind extern determiniert und*
3. *am Ort der Ausführung des Teilprozesses ist eine Kooperation mit aus Prozesssicht externen Ressourcen notwendig.*

Die Definition von Mobilität ist abgeleitet von den Eigenschaften der Aufgabe, welche die prozessausführende Person innerhalb des mobilen Teilprozesses bearbeitet. Es handelt sich dabei also nicht um Mobilität, die durch das Vorhandensein mobiler Technologien erzeugt wird. Demnach kann nach der ersten Annahme vor dem auslösenden Ereignis eines Prozesses der Ort der Ausführung der Aktivität in unterschiedlichen Geschäftsprozessinstanzen divergieren oder sich der Ort während der Ausführung des Teilprozesses ändern. Weiterhin geht die zweite Annahme davon aus, dass die Unsicherheit des Ortes von externen Faktoren festgelegt wird und die prozessausführende Person somit keine Kontrolle hinsichtlich dieses Ortes hat. Die dritte Annahme schränkt den Begriff des mobilen Geschäftsprozesses auf die Notwendigkeit einer Kooperation mit externen Ressourcen innerhalb des betrachteten Teilprozesses ein. Dabei kann es sich um Kommunikations- oder Koordinationsbedarf mit anderen Personen, um einen maschinellen Informationsaustausch oder um eine Interaktion mit anderen Objekten handeln.

4 ANALYSE UND BEWERTUNG DER POTENTIALE FÜR NETZWERKE IN DYNAMISCHEN WERTSCHÖPFUNGSKETTEN UND MOBILE IT-INFRASTRUKTUREN

Das ökonomische Entscheidungsproblem für den Einsatz mobiler Technologien formuliert die Frage nach der Rentabilität einer solchen Investition. Die Basis zur Lösungsfindung liefert eine Analyse der Geschäftsprozesse und der bestehenden Systemumgebung. Es besteht deshalb die Notwendigkeit, dass die Unternehmensabläufe in einem Prozessmodell abgebildet werden, um anschließend, auf Basis der Definition nomadischer Geschäftsprozesse, potentielle Prozesse und deren Änderungen ausfindig zu machen. Die neu konzipierte Prozessstruktur kann dann als Fundament für eine Analyse und Bewertung der Nutzenpotentiale dienen.

4.1 *Konzeption eines Referenzmodells*

Aufgrund des Mangels an vollständig durchgeführten Untersuchungsmethoden soll in dieser Arbeit ein Referenzmdoell entwickelt werden, das eine modellhafte Vorgehensweise für einen abgegrenzten Problembereich beschreibt und für mehrere Einzelfälle anwendbar ist.[26] Es integriert die Abhängigkeiten zwischen Geschäftsprozessen und Technologieeinsatz und will die Potentiale des Nomadic Computing aus betriebswirtschaftlicher Sicht analysieren und bewerten. Die Lösung des Entscheidungsproblems muss dabei im Einklang mit der strategischen

[26] Vgl. Stahlknecht and Hasenkamp (2001).

Zielsetzung stehen. Für dieses Vorgehen sind folgende Schritte notwendig, die in Abbildung J.3 grafisch aufgezeigt werden:

1. Analyse des Geschäftsprozessmodells und Identifikation sowie Klassifikation nomadischer Geschäfts-prozesse. Anschließend erfolgt ein Redesign der identifizierten Prozessteile unter der Annahme der Herstellbarkeit einer nicht näher spezifizierten mobilen Komponente für das Informationssystem und Spezifikation der mobilen Komponente nach Maßgabe der neuen Prozesse.

2. Analyse und Identifizierung von Nutzenpotentialen und Einordnung in Nutzenkategorien.

3. Bewertung der Nutzenpotentiale auch unter wirtschaftlichen Aspekten. Dieser strukturierte Pool von Nutzenpotentialen wird im Rahmen von Wirtschaftlichkeitsbewertungen sowohl unter Risiko- als auch unter betriebswirtschaftlichen Gesichtspunkten bewertet. Dieser Punkt kann im Rahmen einer Investitionsentscheidung als Meilenstein bezeichnet werden. Ziel ist es, eine Entscheidungsgröße zu ermitteln, die ein weiteres Vorgehen - die technische Umsetzungsplanung - begründet.

4. Durchführung der Veränderung (tatsächliches Redesign der Prozesse und Entwicklung der mobilen Komponente) in der Umsetzungsplanung.

Grundlage für die Durchführung ist ein aus fachlicher Sicht erstelltes Geschäftsprozessmodell der zu betrachtenden Unternehmung. Ziel des Vorgehens ist die Handhabbarkeit von Komplexität und die Beschränkung der Prozessanalyse auf die potentiell nomadischen Prozessteile von Anfang an. Das Ergebnis der Analyse kann einerseits als Basis für ein Redesign der Prozesse, andererseits für das Requirements Engineering mobiler Informationssysteme verwendet werden.

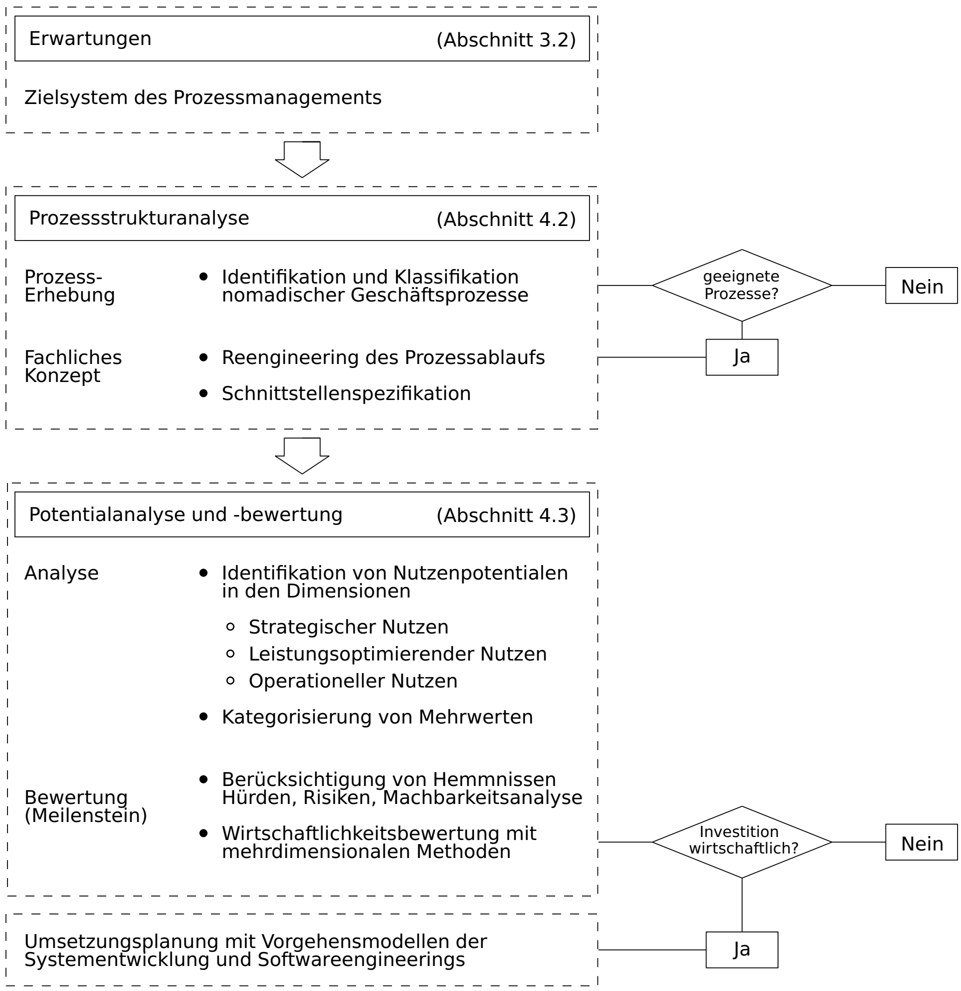
4.2 *Prozessstrukturanalyse*

In einem ersten Schritt werden die Geschäftsprozesse nach dem Mobilitätspotential bzw. nomadischen Charakteristika analysiert, um geeignete Geschäftsprozesse zu identifizieren, zu klassifizieren und neu zu konzipieren. Darüber hinaus können auch neue Geschäftsprozesse entstehen.[27] Das Redesign berücksichtigt anschließend in einem fachlichen Konzept die Prozessausrichtung auf nomadische Technologien.

Für die Identifizierung potentieller Prozesse wird grundsätzlich die Definition nomadischer Geschäfts-prozesse herangezogen. Eine Lösung, um mit Hilfe mobilitätsunterstützender Technologien systematisch innerhalb gewachsener Prozessstrukturen betriebswirtschaftliche Nutzenpotentiale aufzudecken, kann mit

[27] Vgl. Köhler and Gruhn (2004b).

Abbildung J.3: Vorgehen im Referenzmodell zur Potentialanalyse und -bewertung



der Methode des Mobile-Process-Landscaping durchgeführt werden.[28] Mit der Methode des Mobile-Process-Landscaping geschieht ein systematisches Vorgehen, mit Hilfe dessen mobile Prozessanteile identifiziert und analysiert werden können. Da Nomadic Computing im besonderen Maße den Nutzenkontext miteinbezieht, eignen sich Geschäftsprozesse, die zeitlich spontan anfallen und keinen Routine-Charakter aufweisen.

Gegenstand des Process-Reengineering ist die inhaltliche Analyse der identifizierten nomadischen Prozesse sowie die Planung der Neustrukturierung. Dazu muss geplant werden, auf welche Weise nomadische Technologien diese Prozesse unterstützen können, wie z. B. die Prüfung der Möglichkeiten zur Anbindung an Backend-Systeme, der Online-Zugriff auf die benötigten Daten etc. Zusätzlich

[28] Vgl. im folgendem Köhler and Gruhn (2004b). Die Methode wurde am Lehrstuhl für Angewandte Telematik/E-Business der Universität Leipzig entwickelt. In ihrer Arbeit führen sie auch weitere Methoden anderer Methoden auf.

erfolgt eine Schnittstellenspezifikation, welche die Informations- bzw. Datenflüsse zwischen den Elementen der mobilen und der nicht-mobilen Prozessteile beschreibt, die über eine direkte Verbindung miteinander verfügen.[29]

4.3 *Analyse und Bewertung der Nutzenpotentiale*

4.3.1 *Dimensionen der Nutzenpotentiale*

Die Schwierigkeit einer exakten Identifizierung sämtlicher Potentiale liegt in der Tatsache, dass der Untersuchungsraum unbekannt bzw. Ungewissheit über die Dimension von Potentialen des Nomadic Computing besteht. Dimensionen werden in diesem Zusammenhang als Kategorien verstanden, denen sich sachlich zugehörige Nutzenpotentiale zuordnen lassen. Die Festlegung dieser Dimensionen garantiert einen klar abgesteckten Untersuchungsraum, in dem für jede Dimension sämtliche inhaltlich zugehörige Potentiale identifiziert und analysiert werden können. Darüber hinaus könnten Interaktionen und die Möglichkeit der Aggregation von Potentialen innerhalb und ausserhalb einer Dimension hinzugezogen werden. Da die Dimensionen ihrerseits zur Zielerreichung beitragen, sollten sie zu den Zielen des Prozessmanagements - die Prozessoptimierung hinsichtlich Zeit, Kosten, Qualität und Innovation - eine Verbindung aufweisen. Für die in dieser Arbeit verwandten Ziele werden daher folgende Nutzendimensionen mit den Beziehungen definiert:

- Strategische Potentiale sind keine direkt ablesbaren Mehrwerte, sondern schlagen sich in höheren Unternehmenszielen nieder; z. T. werden sie auch von anderen Dimensionen beeinflusst. Beispielsweise ermöglichen technologische Potentiale - angetrieben durch technologische Entwicklungen - bei ihrer Entfaltung innovative und neue Prozesse. Ferner wird auch die Möglichkeit der Integration anderer Technologien als Potential gesehen, wenn sich dadurch höhere Mehrwerte generieren lassen.

- Leistungsoptimierende bzw. quantitativ-messbare Potentiale sind quantitativ messbare Eigenschaften, die sich beispielsweise in Kosten oder Zeit niederschlagen können. Damit können sie auch z. T. monetär bewertbar sein. Diese Form der Potentiale lassen sich relativ leicht als Kennzahlen darstellen.

- Qualitativ-messbare Potentiale tragen zur Leistungserhöhung der Prozesse bei und sind vorwiegend qualitativer Natur - damit auch schwer messbar. Da eine Quantifizierung nicht immer gelingt, müssen bisweilen aufwendigere Methoden für die Erfassung und Erfolgsmessung angewendet werden. Werden alle Mehrwerte optimal im Untersuchungsraum erreicht, so findet eine maximale Nutzenausschöpfung statt.

[29] Vgl. Gruhn (2005); Köhler and Gruhn (2004b).

4.3.2 *Analyse der Nutzenpotentiale*

Die in diesem Diskussionspapier definierten Potentialdimensionen legen daher den Untersuchungsraum für die Analyse von Nutzenpotentialen fest, die im Folgendem für das Nomadic Computing allgemein herausgearbeitet werden. Im Rahmen der Bewertung der Potentiale können geeignete Kennzahlen zugeodnet werden, die eine Bewertung der Potentiale vereinfachen:

Strategische Nutzenpotentiale

Der strategische Nutzen ergibt sich durch die Integration nomadischer Technologien in das übrige DV-Umfeld der Unternehmung, meist in Anknüpfung an bereits vorhandene Systeme und Anwendungen. Dabei ist der strategische Nutzen des Nomadic Computing nicht autonom definierbar, sondern muss aus den Zielen der Unternehmung abgeleitet werden.

Grundsätzlich beschreiben technologische Innovationen primär den technologischen Fortschritt, nicht den betriebswirtschaftlichen Nutzen. So ist die technologische Innovation für eine längerfristige, betriebswirtschaftliche Betrachtung nicht ausreichend. Zur Entwicklung betriebswirtschaftlicher Perspektiven müssen Wertbeiträge neuer Technologien identifiziert werden, welche die gegenwärtigen Geschäftsprozesse verändern oder neue Produkte und Dienstleistungen ermöglichen.[30] Technologische Potentiale sollen bei ihrer Entfaltung innovative und neue Prozesse ermöglichen, angetrieben durch technologische Erweiterungen. Teilweise ermöglichen diese wiederum leistungsoptimierende und qualitative Vorteile. Insofern kann ihnen ein strategischer Charakter zugeschrieben werden. Die folgende Tabelle gibt einen Überblick.

Insbesondere die *Mobilität* wird dabei durch die Vielfalt mobiler Endgeräte erhöht. Um diese Vorteile tatsächlich nutzbar zu machen, müssen spezialisierte Informationssysteme zum Einsatz kommen, die nicht nur den Geschäftsprozess als solches unterstützen, sondern gegebenenfalls auch mit der Mobilität der prozessausführenden Person zurecht kommen sollten.[31] Neuartige Geräteformen wie sogenannte Wearables optimieren insbesondere schwierige Produktionsprozesse und werden teilweise schon heute eingesetzt.[32]

Leistungsoptimierende Nutzenpotentiale

Im Bereich der Kosten lassen sich verschiedene Dimensionen betrachten, die in eine anschließende Nutzenbewertung einfließen. So existieren:

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[30] Vgl. Scheer, A.-W. et al. (2001).

[31] Vgl. Köhler and Gruhn (2004a).

[32] In schwer zugänglichen Bauprojekten, beispielsweise im Schiff- oder Flugzeugbau, werden in smarten Handschuhen Baupläne und Dokumentationen technisch abrufbar; vgl. Herzog et al. (2003).

- *Quantitativ messbare Kosten*, die sich leicht aus den Kostenarten ermitteln lassen, wie Investitions- und Instandhaltungskosten (Hardware/Software), Verbindungsentgelte, Betriebsmittelkosten, etc.
- *Intangible Kosten* sind schwer messbare Kosten, die aber zu den Kostenarten hinzugezählt werden müssen.
- *Koordinationskosten* verkörpern Transaktionskosten, die mit der Anbahnung, Abwicklung und Kontrolle von Prozessen der Leistungserstellung zu tun haben.

Die Wirtschaftlichkeitsanalyse klärt die Fragen, welche Kosten zum Beispiel durch die Neustrukturierung der Prozesse und die Anschaffung technische Geräte entstehen. Gegengerechnet werden die Einsparungen, die sich aus dem Wegfall von Teilaktivitäten, Verkürzung von Bearbeitungszeiten oder Erhöhung der Bearbeitungsqualität ergeben.[33] Im Rahmen der Bewertung kann dann die Frage beantwortet werden, ob die Durchführung des Projektes aus nutzenorientierter Sicht sinnvoll ist.[34] Das Einsparpotential kann bereits bei der Prozessgestaltung errechnet werden, da es sich dabei meist um organisatorische Entscheidungen handelt.

Mit der Fähigkeit, Prozesse auf eine kontinuierliche Weise auszuführen, generiert das Nomadic Computing Vorteile bei der Bearbeitungszeit im Prozessmanagement und damit eine höhere Effektivität. Insbesondere Schnittstellen führen zu erhöhten Bearbeitungs- und Liegezeiten, d. h. die Prozessausführung gestaltet sich als wesentlich langsamer. Mittels Einsatz moderner Technologien wird die Prozesskette verkürzt, aufgrund der durchgängig elektronischen Verarbeitung entfallen Medienbrüche und die Nutzer erhalten orts- und zeitnahe Informationen am Einsatzort.

Qualitativ-messbare Nutzenpotentiale

Der operationelle Nutzen liegt in einer wirkungsvollen Unterstützung der Arbeitsprozesse und kann als Erhöhung der Leistungsfähigkeit beschrieben werden. Mit ihnen wird insbesondere die Qualität der Prozessausführung verbunden. Im Gegensatz zu leistungsoptimierenden Potentialen kristallisieren sich diese Art von Potentialen als schwer messbar, allenfalls nur subjektiv abschätzbar heraus. Als sogenannte „weiche“ Faktoren haben diese meist qualitativen Potentiale indirekte Auswirkungen auf die Prozesskosten und Produktivität. Insbesondere die Berücksichtigung von Zeit, Ort und Personalisierung stellt erhebliche Mehrwerte für die Nutzung nomadischer Technologien dar. Dienste *kontextsensitiver* Qualität von Informationen und Dienstleistungen werden schließlich den Ausschlag geben, ob man bereit ist, für diese Lösung auch zu bezahlen.

[33] Vgl. Köhler and Gruhn (2004a); Köhler and Gruhn (2004b).
[34] Vgl. zum Transaktionskostenansatz Deinlein (2003).

Zusammenfassend weist Nomadic Computing in den drei definierten Nutzendimensionen vielfältige Potentiale aus, die sich unmittelbar und mittelbar auf die Ziele des Prozessmanagements - Effizienz und Effektivität - und damit auch auf höhere Unternehmensziele auswirken. Inwiefern die Nutzenpotentiale in unternehmensspezifischen Prozessen erfolgreich zur Entfaltung gelangen, muss in einer anschließenden Nutzenbewertung analysiert werden. Tabelle J.2 fasst die genannten Nutzenpotentiale noch einmal zusammen.

4.3.3 *Bewertung der Nutzenpotentiale*

Die Bewertungsphase endet mit einem Votum für das Investitionsvorhaben. Innerhalb der gesamten Umsetzungsplanung, welche den anschließenden technischen Entwurf und die Systemplanung integriert, kann dieser Punkt als ein Meilenstein bezeichnet werden. Zweck der Wirtschaftlichkeitbewertung ist es, die Ermittlung der Wirtschaftlichkeit für beliebige Objekte methodisch zu unterstützen. Die Wirtschaftlichkeitsabewertung beschäftigt sich nach Heinrich im eigentlichen Sinn sowohl mit der Analyse der Kostenstruktur, als auch mit der Analyse der Nutzenstruktur und den Kosten- und Nutzenbeziehungen.[35]

Da die Entscheidung meist unter Unsicherheit stattfindet, ist eine solche Bewertung risikoorientiert durchzuführen. Risikofaktoren stellen ein mögliches Hindernis bei der erfolgreichen Einführung oder Betrieb des Nomadic Computing dar.[36] Mögliche Unsicherheiten ergeben sich dabei in folgenden Punkten:

- Sicherheit, Privatsphäre und Rechtliche Risiken,
- Benutzerakzeptanz und -ergonomie und
- Schwachstellen in der Personalisierungsfunktion.

Für Computer-Nomaden, die von wechselnden Aufenthaltsorten aus Zugang zu Netzwerkdiensten bekommen möchten, darf eine Zugangsentscheidung nicht allein auf der Feststellung der Identität getroffen werden, sondern es muss zusätzlich die jeweilige Situation des Anfordernden einbezogen werden: Authentifizierung und Autorisierung sind also klar zu trennen. Die Situation muss durch ein von vertrauenswürdiger Seite ausgestelltes Credential bestätigt werden. Dies kann unter bestimmten Situationen (z. B. Aufenthalt in einem öffentlichen Internet-Café) den Zugang zu bestimmten Diensten oder Daten ausschließen, während er in anderen Situationen (z. B. Aufenthalt bei einem Kooperationspartner) durchaus gestattet wird.[37]

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[35] Vgl. Heinrich (2002).
[36] Vgl. Teubner and Terwey (2005).
[37] Vgl. Luttenberger (2002). Luttenberger stellt in seinem Aufsatz eine Credential-basierte Zugriffskontrolle für das Nomadic Computing vor, die auf einer erweiterten Jini-Architektur aufbaut. Mit geeigneten Protokollen zur Authorisierung in einer nomadischen Umgebung beschäftigt sich auch Zhang and Kindberg (2002).

Tabelle J.2: Nutzenpotentiale

Leistungsoptimierende Nutzenpotentiale	Strategische Nutzenpotentiale	Qualitativ-messbare Nutzenpotentiale
Mehrwerte aus Reduzierung quantitativer Kosten • Material und Sachkosten: Reduzierung von Papier- und Druckkosten durch elektronische Prozessabwicklung • Schnittstellen: Überwindung von Medienbrüchen machen Schnittstellen in Prozessen überflüssig • Reise- und Wegekosten: Daten werden nur noch elektronisch ausgetauscht ⇒ **Messung:** Kostenrechnung	Technisch-innovative Mehrwerte • Innovation: Mobilität, Allgegenwärtigkeit bzw. Ubiquität, Kontextsensitivität (z. B. neue orts- und zeitunabhängige Dienste) • Prozesse: Durchgängigkeit der Prozesse, Systemübergreifende Prozesssteuerung • DV: Vereinigung von Anwendungen und Daten, Realisierung technologisch bedingter Änderungen ⇒ **Messung:** nur in strategischen Projekte messbar	Technische Mehrwerte • Akzeptanz: leicht händelbare Systeme und gute Ergonomie (z. B. Headsets, Wearables) • Funktionalität: neue Eingabemethoden, spontaner Zugriff, auf Person abgestimmte Benutzerschnittstelle • Multimedialität: Verarbeitung unterschiedlicher Formate ⇒ **Messung:** Usability Engineering
Mehrwerte aus Reduzierung Koordinationskosten • Suchkosten: Navigationssystem ermöglicht präzise Ortung auf räumlicher Ebene, Benutzerprofil und Internet ermöglichen schnelle Informationssuche • Kontrollkosten: Kontrollen können systemseitig vorgenommen werden ⇒ **Messung:** Transaktionskostenrechnung	Wettbewerbsfördernde Mehrwerte • Kundenziele: Imagegewinn durch modernen Auftritt, Kundenbindung • Kernkompetenzen: Technische Unterstützung erzeugt z. B. erweiterte Wartungsaufträge durch Einsatz von Sensoren ⇒ **Messung:** Kennzahlen	Mehrwerte aus Diensten • Personalisierung: Bereitstellung von proaktiven Diensten • Kontextsensitiv: Bereitstellung von Situationsinformationen, Lokalisierung von ortsabhängigen Diensten ⇒ **Messung:** Usability Engineering
Mehrwerte aus Reduzierung intangibler Kosten • Datenqualität: sofortige Datenerfassung und Überprüfung • Arbeitsabläufe: sofortige Erfassung von Aufträgen • Informationsfluss: Überwindung von Medienbrüchen, Sofortige Verfügbarkeit (no-boot-time) • Nutzung von Leerzeiten: Arbeitsmöglichkeiten während des Travellings, Visitings und Wanderings ⇒ **Messung:** Prozesskostenrechnung	Organisatorische Mehrwerte • Neue Geschäftsprozesse: Bürolose Mitarbeiter, neue Vertriebswege, Geschäfte können direkt über Endgeräte abgewickelt werden ⇒ **Messung:** Prozesskostenrechnung • Konzentration auf Kernprozesse: Nebentätigkeiten in Prozessen werden zurückgefahren ⇒ **Messung:** Zentralisierungsgrad	Sonstige Mehrwerte • Flexibilität: Ortsunabhängigkeit • Informationseffizienz: Dezentrale Datenhaltung ⇒ **Messung:** schwer messbar • Qualität: Datenqualität, Fehlerquote • Zusammenarbeit: Unterstützung verteilter Zusammenarbeit, Ortung umliegender Objekte ⇒ **Messung:** Kennzahlen

Die Hauptschwierigkeit bei Bewertungen unter wirtschaftlichen Gesichtpunkten besteht allerdings darin, den nicht quantifizierbaren Nutzen in eine Bewertung einzubeziehen. Dies äußert sich insbesondere in der Auswahl geeigneter Bewertungsmethoden. Sogenannte eindimensionale Methoden, die sich auf die klassischen Investitionsverfahren[38] stützen, führen an dieser Stelle zu Schwierigkeiten. Mehrdimensionale Verfahren versuchen die Schwierigkeiten zu überwinden:

1. *Multifaktoren- und Nutzwertanalyse:* Diese Analysemethoden bewerten potentiell nomadischen Prozesse anhand eines Kriterienkataloges, ob ein Einsatz des Nomadic Computing Mehrwerte generieren kann.[39]

2. *Methoden des Prozessmanagements:* Diese Methoden unterstützen die optimale Gestaltung von Geschäftsprozessen. Eine Evaluierung findet insbesondere durch Kennzahlensysteme und der Prozesskostenrechnung statt.[40]

Dazu werden sowohl bei der Multifaktoren- als auch bei der Nutzwertanalyse die Ziele des Prozessmanagements in Teilziele heruntergebrochen und als Zielkriterien definiert. Anhand dieser Zielkriterien werden nun die Alternativen bewertet. Die Kriterien können nach einer Präferenzordnung zusätzlich gewichtet werden. Das Nomadic Computing wird dann mit einer Punktbewertung danach beurteilt, ob es hinsichtlich der einzelnen Kriterien Verbesserungen oder Verschlechterungen gegenüber dem Ausgangszustand bringt.

Mit den Methoden des Prozessmanagements kann parallel mit einem Kennzahlensystem eine Wirtschaftslichkeitsbewertung erfolgen. Im Rahmen der mehrdimensionalen Verfahren ist es insbesondere mit der Balanced Scorecard möglich, zum einen qualitative Größen in Kennzahlen zu transformieren und zum anderen eine laufende Kontrolle während des Betriebs durch die Kennzahlenauswertung zu garantieren. Gleichzeitig bewertet die Balanced Scorecard die Wirkung von IT-Investitionen auf die strategischen Unternehmensziele.

4.4 *Anwendungsszenarien des Nomadic Computing*

Die Grenzen zwischen einzelnen Organisationen werden in Zukunft immer mehr verwischen, und die Unternehmungen werden versuchen an möglichst vielen Stellen mit dem Endkunden in Kontakt zu treten. An den Schnittstellen zum Kunden und externen Partnern können durch das Nomadic Computing neue Prozessstrukturen auftreten, die schon heute teilweise durch das Mobile Computing

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[38] Dazu zählen beispielsweise Return-on-Invest- und Kapitalwertmethoden. Total Costs of Ownership, definiert als Methode zur Identifizierung der Gesamtkosten eines IV-Systems über den gesamten Lebenszyklus, berücksichtigen in Ansätzen qualitative Kostenaspekte; vgl. hierzu Dobschütz (2000).

[39] Zur Anwendung der Multifaktorenmethode vgl. Stahlknecht and Hasenkamp (2001); zur Nutzwertanalyse vgl. Heinrich (2002).

[40] Vgl. zu Methoden des Prozessmanagements Heinrich (2002).

abgedeckt werden. In der Arbeitswelt kann man deshalb innerhalb der Mobilität des Benutzers drei verschiedene Ausprägungen unterscheiden:

- *Travelling:* Als Prozess, sich von einem Punkt zum nächsten zu bewegen.
- *Visiting:* Bedeutet, dass eine längere Zeitperiode an einem Ort verbracht wird, ehe man sich zu einem weiteren Ort bewegt.
- *Wandering:* Mit Wandering wird eine lokal begrenzte Mobilität in einem Gebäude oder begrenztem Gebiet bezeichnet.

Das Untersuchungsfeld „mobile Arbeit“ ist demnach sehr heterogen. Im Folgendem soll die geschäftsprozessorientierte Analyse und Bewertung anhand von zwei charakteristischen Beispielen erläutert werden.

4.4.1 *Vertriebsunterstützung in Dienstleistungsunternehmungen*

In der Vertriebsunterstützung spielt die Mobilität der Mitarbeiter eine immer größere Rolle. Der persönliche Kundenkontakt ist für die Akquisition und Betreuung ein strategischer Erfolgsfaktor geworden. Mobile Technologien können daher die Mobilität des Vertriebsmitarbeiters unterstützen und verkaufsfördernd eingesetzt werden - aber auch ganz neue Vertriebsprozesse und -organisationen erzwingen.[41]

Analyse der Prozessstrukturen

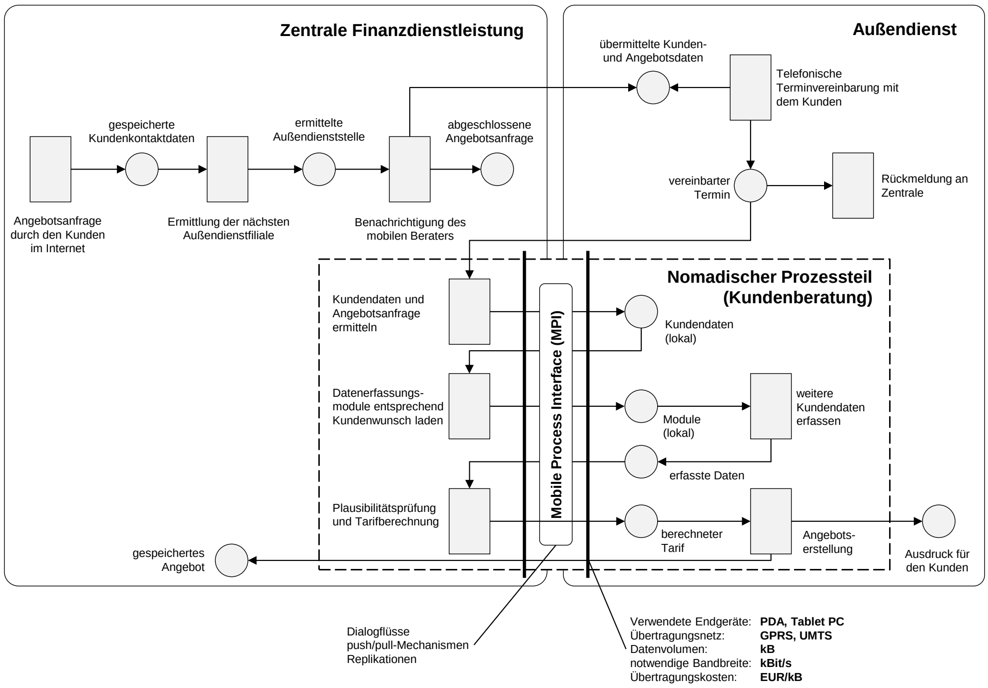
Für die Untersuchung werden nun die Geschäftsprozesse des mobilen Beraters erhoben und abgegrenzt, um potentiell nomadische Geschäftsprozesse herauszufiltern.[42] Die Prozesse Kundengespräch, Akquisition etc. zeichnen sich intuitiv durch ihren mobilen Charakter aus. Die Geschäftsbeziehungen zwischen den Organisationseinheiten im Rahmen des Kundengespräches können als Teilprozesse in einer Prozessmodellierung dargestellt werden.

Aufgabe des *Process Reengineering* ist nun die inhaltliche Analyse der identifizierten nomadischen Prozesse und die Neuplanung dessen, wie mobile Techniken die beschriebenen Prozesse unterstützen können.[43] Gegebenenfalls werden im Rahmen des mobile Process Reengineering Teilaktivitäten neu entstehen oder überflüssig werden. Entsprechend ist eine neue Struktur für den Teilprozess und die an ihn angrenzenden Vorgänge zu planen. Das Kundengespräch wird deshalb als mobiler Prozessteil neu definiert - das Ergebnis zeigt exemplarisch Abbildung J.4.

Aufgrund der hohen Mobilität des Benutzers, der sich außerhalb des Firmengeländes bewegt, sind neben mobilen Geräten auch kabellose Netztechnologien miteinzubeziehen. In diesem Zusammenhang sind anschließend - in Abhängigkeit vom zu übertragenden Datenvolumen und der geforderten Bandbreite - geeignete

[41] Mit der technischen Unterstützung mobiler Arbeiten beschäftigen sich auch Kurbel et al. (2003).
[42] Die Prozessstrukturanalyse konzentriert sich nach einem Beispiel von Köhler and Gruhn (2004a).
[43] Vgl. Gruhn (2005).

Abbildung J.4: Identifikation von mobilen Prozessteilen nach Köhler and Gruhn (2004b)



Endgeräte und Netztechnologien auszuwählen. Der Außendienstmitarbeiter verfügt über die Adressdaten des Kunden und sucht ihn mittel Navigationstechnologie für ein persönliches Beratungsgepräch auf. Vor Ort baut der mobile Berater mit seinem Notebook eine Mobilfunkverbindung zur Zentrale auf und erhält so die vollständigen Daten des jeweiligen Kooperationspartners. So kann er sofort ein verbindliches Angebot berechnen und erstellen, das dann zeitgleich beim Kunden und bei der Zentrale vorliegt.

Die anschließende Potentialanalyse findet im Rahmen aller identifizierten potentiell nomadischen Prozessen statt. Allein an dem Beispiel des klassischen Vertriebsmitarbeiters werden zahlreiche Ineffizienzen erkennbar: Die Belastung anderer Prozessbeteiligter durch ständige Rückfragen, Doppelarbeit und zusätzliche Fehlerquellen durch den Medienbruch und schließlich der Aufwand für den mobilen Berater selbst. In sämtlichen Prozessen im mobilen Vertriebsbereich ergeben sich aufgrund der Mobilitätsformen weitere Nutzenpotentiale. Gleichzeitig können zu den analysierten Mehrwerten zugehörige Kennzahlen ausgewählt werden, die im Rahmen der mehrdimensionalen Wirtschaftlichkeitsbewertungen eingesetzt werden. Nomadic Computing ermöglicht nun die Schaffung einer durchgängigen Prozesskette, in die der mobile Berater vollwertig eingebunden ist.

- Der mobile Berater hat ein mobiles Endgerät mit der Möglichkeit, auf das entfernte Firmennetz zuzugreifen.

- Der Mitarbeiter erfasst direkt beim Kunden die Vertragsdaten.

- Die aufgenommene Bestellung wird durch die mobile Lösung in die Unternehmung übertragen. Rahmenbedingungen wie Verfügbarkeit können umgehend berücksichtigt und dem Kunden mitgeteilt werden.
- Die Auftragsbestätigung erfolgt direkt vom Stammsitz der Unternehmung per Fax bzw. per eMail an den Kunden, so dass der mobile Berater auch keinen Drucker bei sich führen muss. Der Auftrag ist damit auch sofort erfasst.

Gleichzeitig werden häufig auftretende Probleme in diesem Szenario beseitigt. Zum einen erhöht sich die Beratungs- und Datenqualität durch den Einsatz mobiler Geräte. Die Daten können direkt erfasst werden und damit Übertragungsfehler durch Medienbrüche vermieden werden.

Potentialbewertung

Die Bewertung der Potentiale aus betriebswirtschaftlicher Sicht orientiert sich analog einem Referenzmodell an mehrdimensionalen Verfahren. Ob die nomadischen Prozessanteile für Technologien des Nomadic Computing geeignet sind, entscheidet eine Nutzwertanalyse. Neben dem Kundengespräch, können als Alternativen weitere Prozessteile bewertet werden. Zusätzlich kann der in diesem Beispiel erhebliche Investitionsaufwand für den Aufbau der Infrastruktur im Rahmen gesonderter Investitionsverfahren ermittelt werden, die in diesem Artikel nicht vertieft werden können.

4.4.2 *Instandhaltung dezentraler Anlagen durch Nomadic Worker*

Die Instandhaltung ist ein exemplarisches Beispiel für die Potentiale des Nomadic Computing, da sie eine weitgehend mobile Tätigkeit mit einer relativ hohen Informationsdurchdringung ist.[44] Eine Instandhaltung wird mit Daten geplant, anhand der Pläne durchgeführt, protokolliert und anschließend dokumentiert, doch die primäre Aufgabe des Instandhaltungspersonals ist die manuelle Arbeit am Objekt. Hinzu kommt, dass die Umgebungsbedingungen häufig so beschaffen sind, dass weder Papier und Stift noch traditionelle Informationstechnologie eingesetzt werden können und die Benutzer darüber hinaus ihre Hände frei haben und ihre Aufmerksamkeit der realen Welt widmen müssen. Bisher ist diese Inspektion noch ein manueller Prozess, der mit vielen administrativen Arbeiten verbunden ist.

Speziell im Bereich Facility Management sind zahlreiche Nomadic Worker im Einsatz. Eine Vielfalt von Objekt- und Kundeninformationen müssen jederzeit sofort abrufbar sein und Daten werden direkt vor Ort erfasst und müssen danach in zentralen Systemen weiterverarbeitet werden. Bei derartigen Geschäftsprozessen bietet Nomadic Computing ein großes Wertschöpfungspotential und kann zur Unterstützung mobiler Mitarbeiter und als Managementinstrument eingesetzt werden.[45]

[44] Der Bereich der mobilen Instandhaltung ist auch Gegenstand von Herzog et al. (2003); Teuteberg (2005); Hanhart et al. (2005) und Habermann (2005).

[45] Vgl. Frey (2003).

Wartungsszenarien werden, in Verbindung mit Wearables, als ein zukunftsträchtiges Feld für Nomadic Computing gesehen. Durch den Einsatz der Sensortechnologie können in einer weitergehenden Betrachtung menschliche Einwirkungen in den Prozess zurückgefahren werden - damit entstehen Berührungspunkte zum Ubiquitous Computing.

5 ZUSAMMENFASSUNG UND AUSBLICK

Der dargestellte geschäftsprozessorientierte Einsatz des Nomadic Computing konzentrierte sich schwerpunktmäßig auf Nutzenpotentiale, die aus einer betriebswirtschaftlichen Sicht analysiert und bewertet wurden. Aus Sicht der nachfragenden Unternehmungen gilt es zu bewerten, inwiefern ein Einsatz von Nomadic Computing Mehrwerte entlang der Wertschöpfungskette generieren kann.

Intuitiv betrachtet kann eine Ausstattung von Prozessen und Projekten mit Technologien, die das Prinzip „Anytime-anywhere“ unterstützen, als nutzungsgewinn bezeichnet werden. Betriebswirtschaftlich ist die Einbindung von Technologien differenzierter zu bewerten. Oftmals rechtfertigen die Kosten und Risiken nicht den Nutzen oder die Implementierung erweist sich als schwierig. Eine vorausgehende Analyse und Bewertung, die sämtliche Aspekte des Nomadic Computing berücksichtigen kann, erscheint daher unabdingbar.

Die methodengestützte Untersuchung anhand eines Referenzmodells bildet dabei eine transparente Möglichkeit, Nutzenpotentiale in einem festgelegten Rahmen zu untersuchen. Als Vorteile können genannt werden:

- Eine Einbindung in das strategische Zielsystem und damit eine ganzheitliche Steuerung ist möglich.
- Die Schwierigkeit der Quantifizierung kann überwunden werden.
- Die Prozessstrukturanalyse erlaubt eine Optimierung von Prozessen.
- Nutzendimensionen erlauben eine spezifischere Nutzenpotentialbetrachtung.
- Risiken und Hemmnisse werden berücksichtigt.

Gleichwohl kann das hier vorgestellte Referenzmodell nicht sämtliche Felder des Nomadic Computing abdecken. So läßt sich der Untersuchungsrahmen über die Betrachtung hinaus um weitere Analysebereiche erweitern. Daneben können auch noch bestehende Herausforderungen die Zukunftschancen des Nomadic Computing erhöhen.

- Einbeziehung einer soziologischen Perspektive: Die Akzeptanz der Technologie durch die Benutzer garantiert eine weite Verbreitung, die wiederum Auslöser für weitere Mehrwerte bei den Benutzern darstellt.

- Technologischer Fortschritt: Leistungsfähige mobile Geräte, Weiterentwicklung tragbarer mobiler Sensoren.
- Sicherheit: Festlegung von Sicherheitsstandards im mobilen Bereich bleibt ein kritischer Erfolgsfaktor.
- Neue Abrechnungssysteme und Kostenmodelle: Anreizorientierte und verursachungsgerechte Abrechnung der Dienste im Nomadic Computinggarantieren Akzeptanz

An den Schnittstellen zu verwandten Technologien - Ubiquitous Computing, Wearable Computing und Nomadic Computing - zeichnen sich interessante Forschungsfelder ab: Im Bereich der Benutzerschnittstelle stellt Augmented Reality (AR) eine neue Technologie dar. Zur interessanten Basistechnologie des AR zählt unter anderem die Vielfalt der Displays. Die Thematik tragbarer mobiler Sensoren ist sehr zukunftsträchtig und spannt den Bogen von hochgradiger volumeneffizienter Mikrointegration hin zur Elektronik in Kleidung.[46] So helfen im Rahmen des Wearable Computing neue Geräteformen die Mobilität des Benutzers auch im Rahmen des Nomadic Computing zu unterstützen. Insbesondere in den Bereichen der Wartung von Anlagen helfen Wearables mit neuen Möglichkeiten der Benutzerschnittstelle, Arbeitsprozesse effizienter zu betreiben.

Um die Akzeptanz der Benutzer aufrecht zu halten, bedarf es geeigneter *Kosten- und Abrechnungssysteme*. Diese sollen die Realität der Ausführung von Aktionen durch den menschlichen Nutzer in der physischen Umwelt widerspiegeln. Im einzelnen muss untersucht werden, in wie weit dem Nutzer die bereitgestellten Dienste berechnet werden. Denkbar sind schon Lösungen - ähnlich wie bei den Satelliten-Positionierungsverfahren - in dem Dienste im Premium-Segment abgerechnet werden, während abgestufte Varianten der Masse an Benutzern kostenlos zur Verfügung gestellt werden.

Der künftige Einsatz des Nomadic Computing wird sich wohl zunächst im Bereich der Tourismusinformationssysteme und in der Unterstützung mobiler Wartungsprozesse manifestieren. Studien belegen, dass für Toruismusdienste zahlungskräftige Kundschaft akquiriert werden kann. Die Unterstützung von mobilen Arbeitern bei Wartungs- und Produktionsaufgaben steht im Mittelpunkt des Projektes SNOW (Service for Nomadic Workers).[47] Geplant ist ein multimodales Interfaces, mit dessen Hilfe Arbeiter über verschiedene Eingabemodi wie Sprache, Gestik oder Schrift interaktiv auf Dokumentationen vor Ort und über mobile Endgerätezugreifen können. Sie erhalten damit die Möglichkeit in teils schwierigen Arbeitsumgebungen ein „multimediales Wartungs- oder Nutzerhandbuch" zu nutzen und auf Unternehmenswissensdatenbanken zuzugreifen. Bislang existieren allerdings keine Werkzeuge, die die Erstellung mobiler Wartungsdokumentatio-

[46] Vgl. Herzog et al. (2003); vgl. auch Becker and Marrón (2005) und Fekete et al. (2005).

[47] Vgl. Fraunhofer-Institut für Rechnerarchitektur und Softwaretechnik FIRST (2005). Das Projekt startete Ende 2004 und wird von der Europäischen Union gefördert.

nen unterstützen, und es fehlen robuste Interaktionsmöglichkeiten, um solche Dokumentationen zu nutzen.

Part III

BIBLIOGRAPHY

I divide the Bibliography in two separate parts: First, the primarily bibliography contains all references regarding to the main dissertation topic. Second, I move all references of the »Nomadic Computing« paper to a secondary bibliography to face the disjoint research cluster.

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