2007

Real-Time Market Valuation of Options Based on Web Mining and Neurosimulation

P. Bartels
bartels@iwi.uni-hannover.de

Michael H. Breitner
Leibniz Universität Hannover, breitner@iwi.uni-hannover.de

REAL-TIME MARKET VALUATION OF OPTIONS BASED ON WEB MINING AND NEUROSIMULATION

Bartels, Patrick, Institut für Wirtschaftsinformatik, Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany. bartels@iwi.uni-hannover.de

Breitner, Michael, Institut für Wirtschaftsinformatik, Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany. breitner@iwi.uni-hannover.de

Abstract

Today's theoretic, i.e. stochastic, option valuation models, inherently base on unrealistic assumptions. Especially the adequate estimation of a volatility measure is discussed controversially. Several studies show that the issuer's individual volatility measure is used to exploit the consumer surplus. Moreover, not only the well-known inputs but also "hidden" inputs affect option market prices significantly. Therefore alternative options pricing approaches use artificial neural networks to learn market prices models from observed market data. The core question is: Are time-varying artificial neural networks (ANN) based on a high amount of automatically collected market data more accurate and more realistic than classical methods like, e. g., the ones of Black/Scholes or Cox/Ross/Rubinstein? To answer this question the software suite WARRANT-PRO-1 is used which incorporates the web mining agent PISA (Partially Intelligent Software Agent) and the neurosimulator FAUN (Fast Approximation with Universal Neural Networks). In real-time WARRANT-PRO-1 synthesizes ANN market valuation functions of Internet-available data or other (semi-)structured text sources. FAUN trains ANN, e. g., market prices for standard and user defined so called OTC (over the counter) options. Statistical analyses and examples including German DAX warrants and OTC options presented in this article indicate the feasibility of this approach.

Keywords: Options, derivatives, market price models, artificial neural networks, web mining, Black/Scholes model.

1 INTRODUCTION AND MOTIVATION

Risk management is essential in modern market economy. Financial markets enable companies and households to select an appropriate level of risk in their transactions by redistributing risks towards other agents who are willing and able to accept them. Markets for options, futures and other so-called derivative instruments – derivatives for short – have a particular status. Futures allow agents to hedge against upcoming risks. These contracts promise future delivery of a certain item at a certain strike price. Options allow agents to hedge against one-sided risks. Options give the right, but not the obligation, to buy (call option) or sell (put option) something at a predefined strike price at expiration (European style option) or at any time up to expiration (American style option) (see Hull, 2003; Prisman, 2000). All classic analytical models, e.g. Black/Scholes and Cox/Ross/Rubinstein, for option valuation have several constraints regarding accuracy. In this paper we present a generally more accurate approach to option valuation which is fully market oriented (instead of theoretic) with the WARRANT-PRO-1 software suite. It synthesizes market prices for options using the PISA web mining agent and the FAUN neurosimulator. Changing training variables market prices for other derivatives can also be synthesized. The synthesized market prices can be compared with classical models like the ones of Black/Scholes or Cox/Ross/Rubinstein.

Dirk Thiel shows that issuers use individual settings of the volatility parameter within the Black/Scholes formula to control hedging performance of their own options and to exploit the consumer surplus (Thiel, 2001 pp. 223-265). The individual setting is not observable at the market. Therefore related studies use either historical or forecasted volatility measures to estimate the future volatility for market price training. As these are not issuer dependant WARRANT-PRO-1 includes the options' issuers in the market price functions. Integration of a volatility measure is discarded. ANN learn the current volatility out of the presented input values. Thereby companies as well as private investors can compare options of different issuers and/or to single out over- or under-priced ones. Market prices allow option evaluation when options for a certain risk are unavailable simultaneously, e.g. OTC-options.

Current research concentrates on evaluating option pricing models using neural networks with a high amount of training data. For artificial neural network (ANN) training usually commercial data providers like Reuters, Bloomberg and others are used. Most of those only provide a part of the worldwide traded options and the data are usually expansive. Both using commercial data and the amount of used training data reduce practical applicability. In contradiction to common research this paper's major research issue is real-time market price synthesis with practical applicability on common desktop computers. For about one decade both research on web mining and on option pricing with ANN existed separately. WARRANT-PRO-1 is the first attempt known to the authors that combines these two areas of research. It automatically extracts option spot prices from the Internet for free and performs neural network trainings. The software suite can be adjusted to various input data. Input files are of high quality, i. e. outlier free, and have pre-definable denseness. It offers a platform independent suite to calculate highly accurate option market prices in real-time using data from the near past only. The resulting market prices are exemplarily evaluated and compared with the Black/Scholes model. The core question is: Are time-varying Artificial Neural Network (ANN) models based on a high amount of automatically collected market data more accurate and more realistic? For the first time issuer related differences in market prices are evaluated using ANN. An ANN curvature measure for evaluation is used in option pricing with ANN for the first time, too.

To show feasibility of our approach this article proceeds as follows. In section 2 weaknesses of classic option pricing models are discussed in detail and current research on option pricing with ANN is briefly introduced. Section 3 introduces WARRANT-PRO-1 in detail including a short introduction to ANN. Section 4 presents an advanced prototype of the software suite. A test with 141 German DAX call options is used to prove the system's ability to learn market price functions from a single day's intraday data accurately. Afterwards this empiric market price function is evaluated against the Black/Scholes-prices for the given data. Section 5 concludes the article with a summary and an outlook to further research.

2 RESEARCH ON OPTION MARKET PRICES

Option valuation has been a major topic in financial literature for over 100 years now. Today's most popular option pricing formulas were published in 1973 by Fisher Black and Myron Scholes (Black & Scholes, 1973) and 1976 by John C. Cox and Stephen A. Ross (Cox & Ross, 1976a; Cox & Ross, 1976b) and are commonly known as "the classic models of option pricing". Common to both theoretic models is that the correct option price is investigated by an option underlying portfolio with risk free profit. The theoretically fair option price p_{BS} (Black/Scholes) depends on the underlying price S, the strike price X, the time to expiration T, the risk-free interest rate r to expiration and the future volatility σ_s of the underlying price. The latter is estimated by the annualized standard deviation of percentage change in daily price. The Cox/Ross/Rubinstein-model depends on S, X, T and r, too. Future volatility is represented by the likelihood of rising and falling of S in time steps with appropriate length.

Both mentioned analytical models base on at least two well-known problematic assumptions: First, markets are assumed to be efficient so that a prediction of the direction of the market or an individual underlying is not possible. Second, future volatility σ_s of the underlying price is assumed to be accurately estimatable and is a priori known to seller and buyer of an option. Since the volatility in both models is estimated, σ_s "varies" and often neither the Black/Scholes model nor the Cox/Ross/Rubinstein model capture option market prices accurately. Numerous studies have documented sizable and persistent cross-sectional differences in a smile or sneer pattern called "Volatility Smile" (see e.g. Black, 1975; Ederington & Guan, 2005; Rubinstein, 1994). In particular the important option price sensitivities ("Option Greeks") Γ, Θ, Δ, and Ω usually are inaccurate. Numerous researchers focus their research on the evaluation of these classic models (e.g. MacBeth & Merville, 1980; Pape & Merk, 2003; Rubinstein, 1985; Bates, 2003). Results are consistent that the Black/Scholes model has significant shortcomings. Even the originators of the Black/Scholes model admitted that the reason for their model's popularity is not accuracy but ubiquity. Black noticed: "Because the formula is so popular, because so many traders and investors use it, option prices tend to fit the model even when they shouldn't" (Black, 1992, p.21). Since the first publication more advanced models have been developed that take violations of classic assumptions into account and are much more accurate as consequence (For an overview see Hull, 2003 pp. 435-458; Bakshi et al., 1997 pp. 2003-2005). Most approaches focus on specific advancements. As a practical matter, the perfectly specified option pricing model incorporates all advancements and is therefore bound to be too complex for applications.

Therefore researchers focus on ANN that learn market conditions of given data. Most prior studies tried to increase the processed data volume (e. g. Andreou et al., 2002 use more than 80.000 datasets) or opt for very complex topologies (e. g. Hanke, 1999 use 7 input and 50 inner neurons). Usually daily closing prices are used (Andreou et al., 2006; Bennell & Sutcliffe, 2004; Pape & Merk, 2003). A high amount of data and daily quotations extend the data period into the past. Thereby data of market situations are contained within the training data that have only little relevance for current market prices, e. g. the incidents on 09/11. Synchronization of the used option prices and their underlying is problematic. WARRANT-PRO-1 uses current synchronous intraday quotations only. Related research also focuses on evaluating different historical volatility measures to optimize market price approximation (see Andreou et al., 2006). WARRANT-PRO-1 does not use historical volatility measures at all. Like the classic models the market price $p_M(t, S, X, T)$ depends on the permanently available underlying price S, strike price X and time to expiration T. Instead of r and the artificially estimated σ_s the time t is used as direct input for the valuation model. In difference to most closed-form models ANN are applicable not only to options but to most derivatives.

3 WARRANT-PRO-1 SOFTWARE SUITE

3.1 Overview and Concept

The WARRANT-PRO-1 software suite is designed to avoid the weaknesses mentioned above and enables users to profit from the advantages of autonomous web mining and ANN for real-time option valuation without the necessity of high-performance computing and without special skills. The fields of application are versatile, e.g. OTC-options and market price synthesis in risk management. The software suite is Java-based and is still under development. It integrates two research programs of the

Institut für Wirtschaftsinformatik of the Leibniz Universität Hannover: The web mining software agent PISA and the FAUN neurosimulator. The software suite has been tested in detail and already works satisfactorily (Bartels & Breitner, 2004a; Bartels & Breitner, 2004b; Breitner, 2003). The architecture of the complete software suite is illustrated in Figure 1.

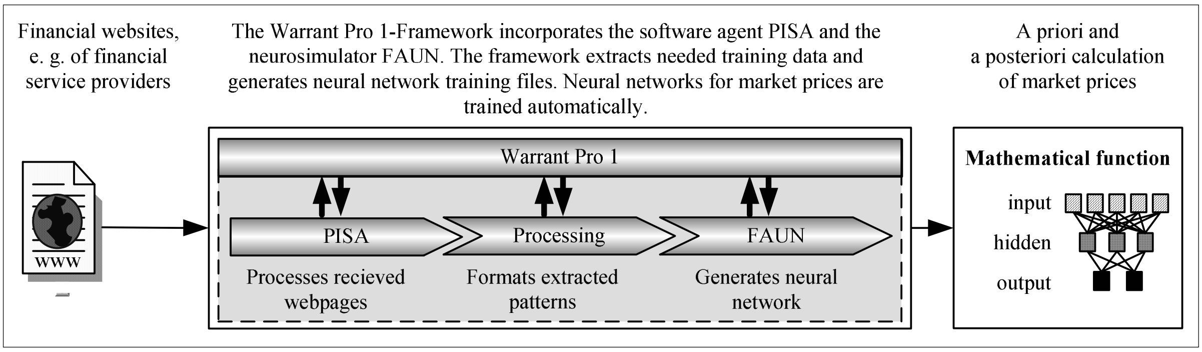

Figure 1. Overview of the WARRANT-PRO-1 software suite, including the web mining software agent PISA and the FAUN neurosimulator.

3.2 Web Mining and the Software Agent PISA

Research on autonomous agents goes back to the 1990ies when Wooldridge and Jennings first discussed the definition of agents (Wooldridge & Jennings, 1995). Primary advantage of using agents is that they can work efficiently 24 hours a day and 7 days a week (except breakdowns and maintenance work). Agents can handle dozens of extraction operations per minute automatically. Therefore software agents are well qualified for web mining tasks.

There are many approaches to utilize agent technology for extracting information from websites. Tredwell, Kuhlins and Irmak, Suel give a detailed overview over existing web mining agents (Tredwell & Kuhlins, 2004 pp. 562-563; Irmak & Suel, 2006). Most agents focus on special perspectives. The requirements of autonomous agents that find and extract derivatives' data within websites efficiently and pre-process the extracted data for neurosimulation are only partially available. Furthermore creating a real-time market valuation tool requires easy usage and fully compatibility to common desktop computers. Many existing agent programs do not have a programming interface, e.g., for SQL (Structured Query Language), and are not platform independent. Therefore the software agent PISA is developed. The full support of multi-threaded design allows PISA to utilize the full advantage of common computers with multiple cores and/or multiple processors.

PISA identifies relevant webpages by the option's International Securities Identification Numbers (ISIN). The websites of major financial service providers are contacted automatically to find the correct webpage. Webpages are repeatedly requested in user-defined intervals. Beside Internet pages any other semistructured or structured text sources are supported, e.g. XML-feeds. The structure of the source code is analyzed automatically to identify the correct information (For further details of the extraction process, see Bartels & Breitner, 2004a; Bartels & Breitner, 2004b).

3.3 Neurosimulation and the FAUN Neurosimulator

ANN in general have a long history in financial applications. They are used for time series forecasts as well as for market simulation and market price synthesis (Andreou et al., 2002; Andreou et al., 2006; Breitner, 2003; Bennell & Sutcliffe, 2004; Garcia & Gencay, 2000). First attempts of market price synthesis with ANN were made in the 1990ies (Hutchinson et al., 1994; Malliaris & Salchenberger, 1993; Malliaris & Salchenberger, 1996). Most research on using ANN for option pricing use the same underlying technology, i. e. so called perceptrons.

An ANN is a collection of interconnected simple processing elements, i. e. input neurons n_i, hidden neurons n_h and output neurons n_o, structured in successive layers – and then called multi-layered perceptron. It can be depicted as a network of arcs/connection and nodes/neurons. Using a propagation algorithm the input values and the inner neurons are weighted to calculate an output value. Within each neuron the given value is processed by an activation function that determines a neuron's output value. 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. An ANN's topology is its specific configuration set including the number of hidden layers, the number of inner neurons in each hidden layer and the propagation and activation function. Each ANN has a specific static topology. The topology defines the approximation capabilities of the ANN. Technically and mathematically training means optimization of topology and weights. A more complex topology increases both approximation capabilities and training effort.

Training quality is highly dependent on the used neurosimulator's learning algorithm. A common and high efficient optimization method is "sequential quadratic programming", SQP for short (Gill et al., 2004). Recently general-purpose SQP methods have been developed that reliably solve constrained optimization problems with many hundreds, thousands or ten thousands of variables and constraints in short time. Therefore SQP is considered superior here. An advanced implementation of SQP is NPSOL (Nonlinear Programming Solver). NPSOL is suitable for mainframes, workstations and PCs, preferably with at least 1MB or more of main storage (Gill et al., 2001). Its efficiency and platform independency makes NPSOL most suitable for real-time market price synthesis. The FAUN neurosimulator incorporates NPSOL and is used therefore. The neurosimulator is being developed since 1996 (Breitner, 2003. For details on ANN and especially perceptrons see Zell, 2003). An exemplary ANN is illustrated in the following figure.

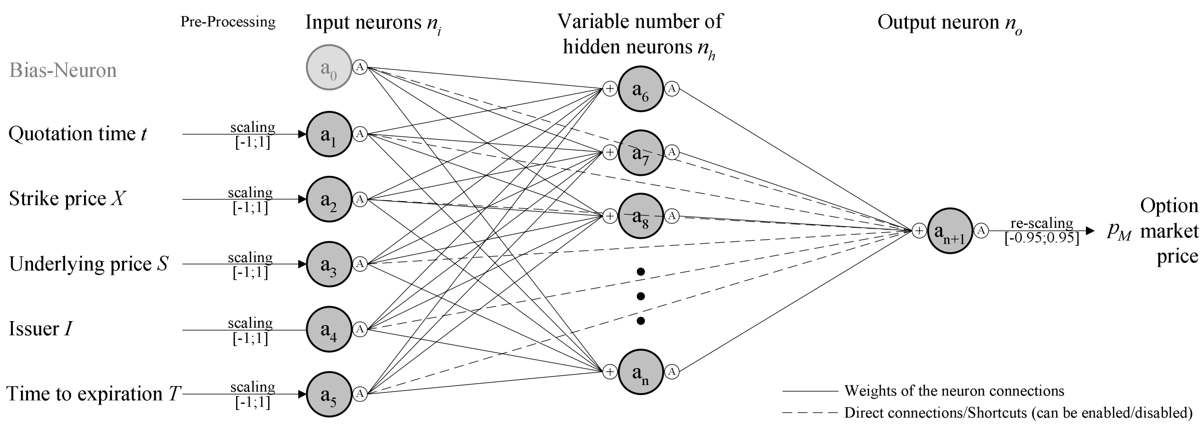

Figure 2. An exemplary Artificial Neural Network's topology (three-layered perceptron) used for market price synthesis in the scenario analyses, here.

The ANN architecture used in this study is a feedforward network with three layers. The first layer includes the four major influencing variables of an option: time t, strike price X, remaining time to expiration T and current price of the underlying S. Additionally networks with each option's issuer I as input value are trained. 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. The second layer has a varying number of hidden neurons. The more inner neurons are processed the better the approximation is but the longer the training takes. The third layer contains only the trained options' market prices p_M. For numerical performance FAUN requires standardized input files. Its activation function, i. e. hyperbolic tangens, requires scaling of the input values. It uses a pre-processing program to scale training and (cross-)validation files automatically. To assure an averaged weight for each strike price and for each issuer the input data are adjusted automatically regarding the number of observations for each strike price and issuer.

Approximation quality of ANN is estimated with the training and (cross-)validation error functions $\varepsilon_t(W)$ and $\varepsilon_v(W)$. W is the matrix of the weights that constitute an ANN. The perceptron is trained iteratively, i. e. ε_t is decreased by adaptation of W, as long as $\varepsilon_v < \varepsilon_t$ or $\varepsilon_v \approx \varepsilon_t$ holds (prevention of overtraining). A quality indicator of a generated ANN is defined, among other criteria, by the (cross-)validation quality, i. e. the quotient of ε_v and ε_t. Both training and validation error are exclusively affected by the used topology, i. e. number of inner neurons and shortcuts activation. Both ε_v and ε_t converge to their lower limit. In this state FAUN calculates the true market price. The differences of the options' spot prices p_S from the trained market price p_M are caused by the issuers' individual pricing methods, i. e. if an option is underpriced or overpriced.

Every ANN is stored in a single file for further analyses. All files can be reloaded or distributed to other users and applied to user given datasets, e. g., for the pricing of OTC-options.

3.4 Real-time Computation of Option Market Prices

WARRANT-PRO-1 is designed to generate real-time market prices that can be used in daily business to generate OTC-option prices or to evaluate an existing option price. Related research usually concentrates either on market simulation or on a posteriori market analyses (Andreou et al., 2002; Bichler & Klimesch, 2000). Other studies use up to 20 different financial indicators as input variables, e.g., trading days vs. calendar days, moneyness ratio and annualized historical volatility with different bases. Our approach uses only five values, i. e. t, S, X, T and I. S and X are replaced by the so called "volatility hint" S/X which is common to related research to reduce training effort. The number of input variables n_i (n_i=3 without issuers and n_i=4 incl. issuers) is directly proportional to both the number of necessary input values and to the number of needed inner neurons n_h in order to achieve adequate networks. Both increase the required training effort significantly. To provide a real-time and easy to use market price synthesis only short training times on common computers are acceptable. Using only few input values allows short training times without corrupting training accuracy.

It is well known that the issuers' calculation of option prices varies in time depending on the implied volatility used (proven for DAX-Options by Thiel, 2001). Including the issuer as input variable the ANN consequently includes an issuer specific calculation approach for market prices.

Related research focuses on cash settlement prices of a long period. The study at hand uses intraday prices instead. Adequacy of intraday prices for option valuation has been tested by several researchers and has been found to be correct. Intraday prices are extracted simultaneously while ANN trainings are conducted to allow WARRANT-PRO-1 to calculate market prices anytime.

4 REAL-TIME MARKET PRICE SYNTHESIS

4.1 Test Scenario and Environment

The presented test for real-time option market prices includes 141 European call options on the major German index DAX. All examined options have an expiration date in June 2006. Data are extracted between 9:00 am and 8:00 pm during May 2006. At 5:45 pm the cash price of the underlying asset, i. e. DAX, is determined. The training data only consist of prices observed between 9:00 am and 5:45 pm. The test is executed on a common desktop computer. In operational use WARRANT-PRO-1 calculates p_M instantaneously. Then trainings are executed either on time schedule or user initiated using only one topology to adjust the ANN to the current market situation. In this paper the ANN training is not processed in real-time because multiple topologies are trained and analyzed.

4.2 Selection and Download of Option Prices

The major influencing variables of option prices are identified above, i. e. p_S, including bid- and ask-price, t, X, S, T and I. Training patterns are extracted semi-automatically from the Internet. For every option static option characteristics are extracted once, i. e. security identification number, X, expiration date and I. Only p_S and quotation time t are extracted frequently to minimize processor load.

Training data should not have any data gaps. Data gaps are caused by poor quality of the offered data and by poor webserver availability. Prior tests showed that a few hundred or thousand training values are enough for an option price synthesis (Bartels & Breitner, 2004c; Breitner, 2003). A further increase of input data does not lead to significant enhancements. This determines the extraction interval to use. Here, all values for the options are alternately extracted every 20 minutes from the Onvista website (http://www.onvista.de) and Finanztreff (http://www.finanztreff.de). Onvista is market leader at financial real-time quotes. Both providers offer real-time quotes from the European Warrant Exchange (EUWAX) in Stuttgart. All other HTML formatted websites can be used as well. Long-term tests have shown that both websites did not have any webserver breakdowns and offer high and reliable data. The underlying asset is the German stock index DAX. Index options are used in many related studies as have a high liquidity. DAX values are alternately extracted from multiple websites.

The minimal number of training patterns is determined by experience. Availability of options with a reasonable moneyness and their update frequency determine the required size of the time slot used for ANN training. Two hours are usually enough to build up an adequate database. For experienced users WARRANT-PRO-1 is able to create training files for every given time slot. The EUWAX offers 221 different DAX call options with a strike price within a spread of 10% out of the money and in the money, i. e. between 5,700 and 6,500, and with an expiration date in June 2006. Filtering the options with an adequate number of observations 141 options of the major 10 issuers remained. Only these were extracted.

Note that extraction and usage of Internet data requires special regards towards legal aspects. Usually the general terms and conditions of financial service providers impose legal restrictions to the usage of the published data. Usage is restricted to private or scientific purposes.

4.3 Pre-Processing of the Training and (Cross-)Validation Data

Option prices are joined with their related price of the underlying and the static option values to build the training patterns. All used quotations are time synchronous. The five possible input variables for ANN training are: time t, strike price X, price of the underlying S, issuer I and time to expiration T, see section 3.4. Instead of using S and X as separate values the so called "volatility hint" S/X is used. Several studies show that this increases training performance significantly (Breitner, 2000 p 320; Andreou et al., 2006 p 332; Hutchinson et al., 1994 pp. 864-868). Contrary to most related research the real time to expiration is used instead of complicated alternatives like the remaining trading days or the 360-day-basis used by banks. Randomly chosen alias numbers substitute issuers' names. Other alias numbers would suggest a linear correlation that is unrealistic.

As output value for ANN training the observed market price p_S is used. Additionally the theoretical Black/Scholes price is calculated $p_{BS}(S, X, T, r, \sigma)$ for each input for evaluation. Other theoretical option pricing models are also supported, e.g., Binomial trees, Monte-Carlo simulations. The risk free interest rate r and the volatility of the underlying σ are not directly observable on the market. For r the Euribor interest rate for the related maturity is used. For σ the estimated value is used that gives the Black/Scholes option prices the best fit to p_S regarding the used evaluation criteria, i. e. the mean absolute percentage error (MAPE). Therefore σ is optimized regarding MAPE. In related research either historical volatilities or forecast volatilities are used. All option prices are standardized to equity exchange ratio since the Black/Scholes formula provides the price for an option of one underlying asset.

To evaluate the training process a validation dataset is used. PISA automatically splits the values into training and validation files. 20% of the data are used for validation. Validation patterns consist of five uniformly distributed segments with an equal number of patterns each. Two training scenarios are processed. For real-time simulation training files are generated every 30 minutes for a time slot of two hours. Additionally for evaluation purposes training files for the whole day are generated for each issuer using only four input variables.

4.4 Training Process and Adequate ANN Topology

For ANN training a three-layered perceptron is used. The arbitrary accuracy of an ANN is only obtained by the used topology. Topologies differ in the number of inner neurons and activation of shortcuts. In the article at hand topologies with a number of inner neuron from 2 to 6 are used, each with and without shortcut connections. Prior studies have shown that ANN with only few inner neurons can adequately approximate even complex market price functions and have the optimal ratio between training effort und output quality. ANN with a higher number of inner neurons tend to have highly frequent oscillations. Experience leads to a recommended number of successfully trained networks between 100 and 1000. This is quite enough for problems even more complex. Trainings are aborted if cross-validation quality is inadequate. For each trained ANN ε_v exceeds ε_t by 5% per pattern at most.

Consistent with related research the training results are evaluated using the coefficient of determination (R^2), the mean absolute percentage error (MAPE) and the root mean square error (RMSE). Results of every training process are saved for further analyses. WARRANT-PRO-1 supports export and import of stored networks using text and spreadsheet files, e.g., Microsoft Excel.

5 RESULTS

5.1 Extraction

About 4,000 datasets with a size of 1.2 Megabyte are extracted each day. The extraction process with PISA works satisfactorily. The generated datasets are of high quality and no data gaps occur. The extracted data/patterns are applicable for ANN training. The given environment even offers the possibility to shorten extraction intervals and to process more webpages. A shorter time interval is not reasonable: Changes of the extracted values are too small then.

The average size of a processed webpage is 30 kilobyte. Using a time delay of 2 seconds between the requests an average transfer rate of 15 kilobytes per second is required for the extraction. This means that an ordinary ISDN connection with two channels and together up to 128 kilobit/s is suitable to use WARRANT-PRO-1. Current UMTS connections even have a usual bandwidth of up to 384 kilobit/s and more using HSDPA. Thus the software suite can be used on mobile devices as well, e.g., by mobile employees of issuers at their customer's site.

5.2 ANN Evaluation

ANN approximate a market price function for given input values. As described above ANN quality is measured by ε_t, ε_v, MAPE, RMSE and R^2. In a state where ε_t and ε_v converge to their lower limit a positive difference between p_S and p_M indicates an option price above the market price p_M and vice versa. For analytical outcomes the dependencies of p_S, p_M and p_{BS} are analyzed.

For real-time option valuation the ANN's approximation capabilities are very important. The training error ε_t decreases with an increase of the number of trained networks as well as with the number of inner neurons. The number of trained networks is set high enough by experience to assure that an adequate good network for each topology is found. With more than six inner neurons an increase of used inner neurons only results in marginal improvements of ε_t and ε_v but in tedious increases of the necessary training time. ε_t and ε_v are near to their lower limit with only six inner neurons. Table 1 illustrates the results of four ANN with six inner neurons as an example. The first two use only three input neurons (*t*, *S/X*, *T*) whereas the second two use the issuer *I* as fourth input value (*t*, *S/X*, *T*, *I*). Each set of neurons is processed with and without shortcuts. Comparison of these topologies shows that shortcuts do not lead to a significant advantage regarding the output measures. It is noticeable that including the Issuer *I* as input parameter results in a superior coefficient of determination. Prior research of the authors has shown that activation of shortcuts is not advantageous for option pricing, see also Table 1.

Shortcuts	n_i	ε_t	ε_v	Curvature	$MAPE_M$	$RMSE_M$	R^2_M	$MAPE_{BS}$	$RMSE_{BS}$	R^2_{BS}
no	3	31.43E-02	31.90E-02	1786.75	1.67E-02	7.47E-04	99.89E-02	4.00E-02	2.64E-03	99.79E-02
yes	3	34.73E-02	36.16E-02	1698.30	1.60E-02	7.85E-04	99.88E-02	4.05E-02	2.62E-03	99.82E-02
no	4	39.88E-02	41.17E-02	1347.12	1.68E-02	8.41E-04	99.96E-02	3.97E-02	2.61E-03	99.80E-02
yes	4	51.63E-02	48.39E-02	3706.24	1.78E-02	9.94E-04	99.24E-02	4.67E-02	8.04E-03	98.94E-02

Table 1. Statistical results for the best of each training with six hidden neurons for May 11, 2006, and 1000 training iterations each.

Curvature is a measurement for the generalization abilities of an ANN (For details on the curvature measure, see Breitner, 2003, p. 93). The curvature has never been used in option pricing with ANN in the literature before. High curvature indicates that the ANN fits the given training and validation data well but oscillates which indicates low generalization abilities. The used curvature measure is scaled linearly. The smallest curvature is realized using four input neurons (including issuers) and without shortcuts. Choosing a specific ANN beside ε_t or ε_v curvature should be considered as criterion.

The second criterion for applicability of the WARRANT-PRO-1 software suite is the time needed for successful training. Training times are almost linearly depending on the number of trained networks.

Larger networks take too much processing time in operational use. Moreover many high frequent oscillations occur which result in outliers and poor generalization capabilities. Training times can be significantly reduced if the initializing boxes for the weights are optimized. An optimized training for the best identified network, i. e. four input neurons, six inner neurons and no shortcuts, takes only minutes on a common desktop computer.

5.3 Real-time Market Price Synthesis

As shown in the previous section including the issuer as an input parameter leads to a superior market price function. To evaluate the ANN only the superior ANN as described above are considered, i. e. using the issuer as fourth input neurons, six hidden neurons, no shortcuts used. Both p_M calculated by the ANN and the artificially calculated p_{BS} are evaluated by their relative deviation of the observed prices p_S. It is noticeable that the distribution of the deviation of p_{BS} and p_S is significantly right-skewed for the used volatility measure. Volatility is optimized regarding MAPE, here. Few significantly poor priced options for certain deep-out-of-the-money strike prices cause the observable shift in the distribution. Note that an alternative approach of volatility optimization for p_{BS} might produce different results, e.g., priori outlier elimination might result in a more suitable distribution. Figure 3 illustrates the percentage errors of p_M and p_{BS} compared to p_S for May 11 2006.

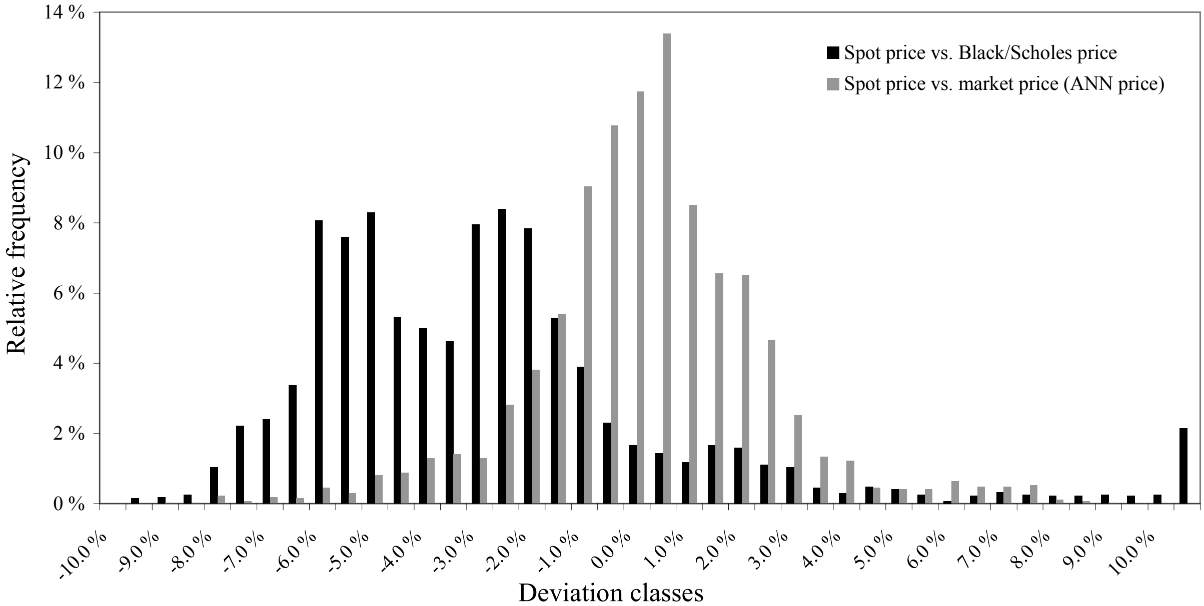

Figure 3. Histogram of the relative deviation of p_{BS} and p_M of the observed prices p_S.

Quality of ANN is determined by the appearance of outliers that interfere with both market prices and reliability. ANN trainings are free of outliers. Analyses indicate that options that are deep out-of-the-money have market prices that significantly differ from the market valuation model. Relative deviations are shown for each issuer in Table 2. This is consistent with other research which claims that the Black/Scholes model overprices out-of-the money options significantly (see e. g. Black, 1992; Cox & Ross, 1976b; MacBeth & Merville, 1980; Pape & Merk, 2003). Reasons for individual issuer specific pricing of theses options are discussed in detail by Thiel (Thiel, 2001 pp. 223-265). Major reason is the small trading volume that initiates issuers to control customer behavior using an individual volatility. Because of the low trading volume there are only few prices available. Deep out-of-the-money options are underrepresented in the training. Beside deep out-of-the-money options WARRANT-PRO-1 calculates p_M for at-the-money and in-the-money options adequately.

The training process is fast enough to calculate p_M near real-time. Therefore the market price function can be used to separate expensive options. As shown by related research issuers use the volatility to control market behavior and options' trading volume to adjust them to their own hedging preferences. Analyses of the correlation between input variables and resulting price difference indicate only small correlations between issuers and outliers. Issuers' pricing preferences change in time. Thus R^2 does not indicate a significant correlation. The market price synthesis offers the possibility to calculate issuer specific prices just-in-time at the moment of a purchasing decision even if no comparable prices are observable. Furthermore it allows to single out over- and underpriced options. The issuer specific mean relative deviations from p_S are shown in Table 2.

	In-the-money					Out-of-the-money			
Issuer	**5700**	**5800**	**5900**	**6000**	**6100**	**6200**	**6300**	**6400**	**6500**
Commerzbank	0.68 %	0.39 %	1.93 %	1.00 %	1.46 %	2.34 %	4.39 %	4.74 %	-21.46 %
Sal. Oppenheim	-0.68 %	-0.39 %	-0.99 %	-2.16 %	-2.20 %	-1.96 %	-0.29 %	-1.89 %	-60.41 %
BNP Paribas	0.16 %	0.66 %	0.90 %	0.81 %	0.81 %	2.46 %	4.90 %	2.67 %	-17.92 %
Goldman Sachs	-1.94 %	-0.41 %	0.10 %	-0.86 %	-2.86 %	-1.04 %	-4.77 %	-6.90 %	-32.93 %
Deutsche Bank	-0.57 %	0.04 %	0.05 %	-0.74 %	0.05 %	1.38 %	4.03 %	5.95 %	-17.84 %
Uni Credito	-1.05 %	-0.38 %	0.49 %	-1.44 %	-3.25 %	2.11 %	3.47 %	7.21 %	-35.23 %
Citibank	0.84 %	0.25 %	0.03 %	0.02 %	0.32 %	0.79 %	-2.35 %	3.11 %	-18.41 %

Table 2. Mean percentage difference of p_S and p_M for selected issuers (six hidden neurons used) for May 11, 2006. In-the-money options are priced more precisely.

6 CONCLUSIONS AND OUTLOOK

The web mining software agent PISA and the FAUN neurosimulator used in combination offer a wide range of important financial applications. For the first time both approaches are combined in the software suite WARRANT-PRO-1 for real-time option pricing. Financial market data are extracted from the Internet to synthesize ANN market valuation functions. A feasibility test for German DAX call options is presented in this article. Financial market data are extracted efficiently and are of high quality, i. e. the data have no data gaps and no outliers. The neurosimulator reliably trains ANN market price functions in real-time with various topologies which are evaluated automatically. Unlike other research approaches the ANN approach does not include estimated future volatility functions or interest rates. In contrast to theoretical option valuation models the heuristic ANN model learns market price functions from observed option prices only. For example buyers or sellers can single out overpriced and underpriced options a priori or a posteriori (interpolation/extrapolation of market data). Issuers can price (OTC-)options for ordinary underlying assets just-in-time and after a few minutes of (semi-)automatic computation for other underlying assets, too. A comparison to the classic Black/Scholes model shows significantly improved accuracy of the ANN market price model.

A test with 141 German DAX call warrants shows that the trained ANN calculate prices for relevant options satisfactorily. Analyses of the calculated market prices also validate research results of others: The Black/Scholes model clearly tends to overprice out-of-the-money options. Additionally for the first time warrant issuers are used as input to determine issuer specific deviations from market prices. Some specific issuer deviations are identified exemplarily based on the ANN model. All singled out computations are real-time or near-time capable.

Future research will focus on longer observation periods. Additionally the ANN training will be further optimized regarding the needed training times. The usability of WARRANT-PRO-1 will be increased, i.e. more statistical analyses, more interfaces to common analysis software like spreadsheet programs and more advanced ANN option pricing models for evaluation will be realized in the near future.

References

Andreou, P., Charalambous, C. and Martzoukos, S. (2006) Robust Artificial Neural Networks for Pricing of European Options. *Computational Economics* 27 (2-3), 329-351.

Andreou, P. C., Charalambous, C. and Martzoukos, S. H. (2002) Critical Assessment of Option Pricing Methods Using Artificial Neural Networks. In *Lecture Notes in Computer Science*, pp 1131-1136, Springer, Berlin.

Bakshi, G., Cao, C. and Chen, Z. (1997) Empirical Performance of Alternative Option Pricing Models. *Journal of Finance* 52 (5), 2003-2049.

Bartels, P. and Breitner, M. H. (2003) Automatic extraction of derivative market prices from webpages using a software agent. IWI Discussion Paper Series # 4, 32 p., Universität Hannover, Institut für Wirtschaftsinformatik.

Bartels, P. and Breitner, M. H. (2004a) Finance applications with the web mining software agent PISA. In Impulse aus der Wirtschaftsinformatik: 5. Liechtensteinisches Wirtschaftsinformatik-Symposium, pp 135-149, Physica-Verlag, Liechtenstein.

Bartels, P. and Breitner, M. H. (2004b) Financial Market Web Mining with the Software Agent PISA. In *Operations Research 2003*, pp 467-474, Springer, Berlin.

Bartels, P. and Breitner, M. H. (2004c) WARRANT-PRO-1: Market Price Synthesis with a Software Agent and a Neurosimulator. *Discussion Paper # 300*, 22 p., Universität Hannover, Wirtschaftswissenschaftliche Fakultät.

Bates, D. S. (2003) Empirical option pricing: a retrospection. *Journal of Econometrics* 116 (1-2), 387-404.

Bennell, J. and Sutcliffe, C. (2004) Black–Scholes versus artificial neural networks in pricing FTSE 100 options: Research Articles. *Intelligent Systems in Accounting, Finance and Management* 12 (4), 243-260.

Bichler, M. and Klimesch, R. (2000) Simulation multivariater Auktionen - Eine Analyse des OTC-Handels mit Finanzderivaten. *Wirtschaftsinformatik* (3), 244-252.

Black, F. (1975) Facts and Fantasy in the Use of Options. *Financial Analysts Journal* 31 (4), 36-41.

Black, F. and Scholes, M. (1973) The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81, 637-659.

Black, F. E. A. (1992) *From Black-Scholes to Black Holes.* Risk Books, London.

Breitner, M. H. (2000) Heuristic Option Pricing with Neural Networks and the Neurocomputer Synapse 3. *Optimization* (47), 319-333.

Breitner, M. H. (2003) *Nichtlineare, multivariate Approximation mit Perzeptrons und anderen Funktionen auf verschiedenen Hochleistungsrechnern.* 530 p., Akademische Verlags-Gesellschaft, Berlin.

Cox, J. C. and Ross, S. A. (1976a) A Survey of Some New Results in Financial Option Pricing Theory. *Journal of Finance* 31 (2, Papers and Proceedings of the Thirty-Fourth Annual Meeting of the American Finance Association Dallas, Texas December 28-30, 1975), 383-402.

Cox, J. C. and Ross, S. A. (1976b) The Valuation of Options for Alternative Stochastic Processes. *Journal of Financial Economics* 3, 145-166.

Ederington, L. and Guan, W. (2005) The information frown in option prices. *Journal of Banking & Finance* 29 (6), 1429-1457.

Garcia, R. and Gencay, R. (2000) Pricing and hedging derivative securities with neural networks and a homogeneity hint. *Journal of Econometrics* 94 (1-2), 93-115.

Gill, P. E., Murray, W., Saunders, M. A. and Wright, M. H. (2001) User's Guide for NPSOL 5.0: A Fortran Package for Nonlinear Programming. Department of Mathematics, University of California, San Diego, La Jolla, California, p 45.

Gill, P. E., Murray, W. and Wright, M. H. (2004) *Practical optimization.* Elsevier Acad. Press, Oxford.

Hanke, M. (1999) Neural Networks vs. Black/Scholes: An Empirical Comparison of Two Fundamentally Different Option Pricing Methods. *Journal of Computational Intelligence in Finance* 7 (1), 26-34.

Hull, J. C. (2003) *Options, Futures & other Derivatives.* Prentice-Hall International, Upper Saddle River, NJ.

Hutchinson, J. M., Lo, A. W. and Poggio, T. (1994) A Nonparametric Approach to Pricing and Hedging Derivative Securities Via Learning Networks. *Journal of Finance* 49 (3, Papers and Proceedings Fifty-Fourth Annual Meeting of the American Finance Association, Boston, Massachusetts, January 3-5, 1994), 851-889.

Irmak, U. and Suel, T. (2006) Interactive wrapper generation with minimal user effort. In *Proceedings of the 15th international conference on World Wide Web*, ACM Press, Edinburgh, Scotland.

Macbeth, J. D. and Merville, L. J. (1980) Tests of the Black-Scholes and Cox Call Option Valuation Models. *Journal of Finance* 35 (2), 285-301.

Malliaris, M. and Salchenberger, L. (1993) A neural network model for estimating option prices. *Applied Intelligence* 3 (3), 193-206.

Malliaris, M. and Salchenberger, L. (1996) Using neural networks to forecast the S&P 100 implied volatility. *Neurocomputing* 10 (2), 183-195.

Merton, R. C. (1998) Applications of Option-Pricing Theory: Twenty-Five Years Later. *American Economic Review* 88 (3), 323-349.

Pape, U. and Merk, A. (2003) Zur Angemessenheit von Optionspreisen: Ergebnisse einer empirischen Überprüfung des Black/Scholes-Modells. *ESCP-EAP working paper 4*, ESCP-EAP, European School of Management, Berlin.

Prisman, E. Z. (2000) *Pricing Derivative Securities: An Interactive, Dynamic Environment with Maple V and Matlab.* Academic Press, San Diego.

Rubinstein, M. (1985) Nonparametric Tests of Alternative Option Pricing Models Using All Reported Trades and Quotes on the 30 Most Active CBOE Option Classes from August 23, 1976 through August 31, 1978. *Journal of Finance* 40 (2), 455-480.

Rubinstein, M. (1994) Implied Binomial Trees. *The Journal of Finance* 49 (3), 771-818.

Thiel, D. (2001) *Die Bewertung von Call-Optionsscheinen auf den deutschen Aktienindex (DAX): eine theoretische und empirische Analyse des Black & Scholes-Modells auf Basis von Intraday-Daten.* Josef Eul Verlag, Lohmar.

Tredwell, R. and Kuhlins, S. (2004) Wrapper Development Tools. http://www.wifo.uni-mannheim.de/~kuhlins/wrappertools/. Last accessed: 12.06.2006.

Wooldridge, M. J. and Jennings, N. R. (1995) Intelligent agents: Theory and Practice. *The Knowledge Engineering Review* (10), 115-152.

Zell, A. (2003) Simulation neuronaler Netze. Oldenbourg, München.