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Surveying stock market forecasting techniques – Part II: Soft computing methods

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ABSTRACT

The key to successful stock market forecasting is achieving best results with minimum required input data. Given stock market model uncertainty, soft computing techniques are viable candidates to capture stock market nonlinear relations returning significant forecasting results with not necessarily prior knowledge of input data statistical distributions. This paper surveys more than 100 related published articles that focus on neural and neuro-fuzzy techniques derived and applied to forecast stock markets. Classifications are made in terms of input data, forecasting methodology, performance evaluation and performance measures used. Through the surveyed papers, it is shown that soft computing techniques are widely accepted to studying and evaluating stock market behavior.

1. Introduction

Stock market forecasters focus on developing approaches to successfully forecast/predict index values or stock prices, aiming at high profits using well defined trading strategies. The central idea to successful stock market prediction is achieving best results using minimum required input data and the least complex stock market model.

Undoubtedly, forecasting stock returns is difficult because of market volatility that needs be captured in used and implemented models. Accurate modeling requires, among other factors, consideration of phenomena characterized, for instance, by recession or expansion periods, and high- or low-volatility periods. Observed volatility in stock market returns/prices arises from the fact that desirable (required) rates of return are themselves highly volatile, driven by cyclical and other short-term fluctuations in aggregate demand. Recent advances in soft computing techniques offer useful tools in forecasting noisy environments like stock markets, capturing their nonlinear behavior.

This research focuses on applications of currently available intelligent techniques to forecast stock market indexes and stock prices. A stock market index represents the movement average of many individual stocks; an index reflects mainly market movement rather than movement of a stock. Firm characteristics are not taken into consideration in the forecasting process. To overcome this limitation, researchers have developed models to forecast individual stock prices. As such, soft computing techniques may be and they have been applied to diverse markets to forecast either indexes or stocks, regardless of their daily trading volume.

Therefore, the purpose of this research is to review and classify derived and applied soft computing techniques to stock market problems; in particular, over 100 related scientific articles applied to stock market forecasting have been reviewed. Results are presented in terms of five summary tables. The first table lists the respective stock markets authors have modeled. The second table lists input variables (independent variables) to the stock market model. The third table summarizes specific methodologies and model parameters used in each paper to forecast stock markets. The fourth table demonstrates modeling benchmarks of each author's specific approach, as well as any comparisons/discussions made against other techniques; such techniques include artificial neural networks (ANNs), linear and multi-linear regression (LR, MLR), ARMA and ARIMA models, genetic algorithms (GAs), random walk (RW), buy and hold (B & H) strategy, and/or other models. The last table summarizes performance measures used to evaluate each surveyed model.

The contribution of this research is a cohesive presentation and classification of soft computing techniques applied to different stock markets that may be used for further analysis and evaluation, as well as comparative studies. An obvious benefit of this study is that if one applies the specifically derived models to the same stock market, stock(s) and/or portfolio(s), valuable results will be obtained, which, when analyzed, may offer additional information to market behavior, correlation among factors influencing performance, input data sensitivity, among other things.

2. Surveyed stock markets and related data sets

The list of stock markets authors have obtained their data for training and testing of their perspective models is shown in Table 1.

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Surveyed articles focus on forecasting returns of a single stock market index or of multiple stock market indexes. However, several studies concentrate in forecasting returns of a single stock or multiple stocks (Ajith, Baikunth, & Mahanti, 2003a; Atsalakis & Valavanis, 2006a, 2006b).

Articles in Table 1 may be classified in three categories. The first category includes articles that use as input data indexes from well developed markets in Western Europe, North America and other solid economy countries.

Ettes (2000), Setnes and Van Drempt (1999) model the Amsterdam stock exchange. Brownstone (1996), Kanas and Yannopoulos (2001) model the FTSE stock index. Lendasse, De Bodt, Wertz, and Verleysen (2000) studies the Belgian market. The Madrid stock exchange is examined by Fernandez-Rodriguez, Gonzalez-Martel, and Sosvilla-Rivebo (2000), Perez-Rodriguez, Torrab, and Andrada-Felixa (2004). The German DAX is forecasted by Rast (1999), Schumann and Lohrbach (1993), Siekmann, Gebhardt, and Kruse (1999), Steiner and Wittkemper (1997). These markets belong to well developed European markets.

Baek and Cho (2002), Chun and Park (2005), Kim and Chun (1998), Kim (1998), Oh and Kim (2002) model the Korean stock index. Cao, Leggio, and Schniederjans (2005), Yiwen, Guizhong, and Zongping (2000), Zhang, Jiang, and Li (2004), Zhongxing and Liting (1993) examine the Shangai stock market. Lam (2001) forecasts the Hong Kong stock exchange, Chen, Leung, and Daouk (2003), Kuo (1998), Wang (2002), Wang and Leu (1996) study the Taiwan stock index. Baba and Kozaki (1992), Huang, Nakamori, and Wang (2005), Jaruszewicz and Mandziuk (2004), Kimoto, Asakawa, Yoda, and Takeoka (1990), Mizuno, Kosaka, and Yajima (1998) forecast the Japanese Stock.

Ajith et al. (2003a), Ajith, Sajith, and Sarathchandran (2003b), Chen, Abraham, Yang, and Yang (2005a) attempt to forecast the NASDAQ stock exchange, and Chaturvedi and Chandra (2004), Halliday (2004), Leigh, Paz, and Purvis (2002) try to forecast the NYSE. The S&P 500 has the highest percentage of preference among studies as in Armano, Marchesi, and Murru (2004), Casas (2001), Malliaris and Salchenberger (1993), Tsaih, Hsu, and Lai (1998). Olson and Mossman (2003) studies the Toronto stock exchange index. Surveyed markets are the North America well developed markets. This survey includes also studies from the Australian Stock Index, surveyed by Barnes, Rimmer, and Ting (2000), Pan, Tilakarante, and Yearwood (2005), Vanstone, Finnie, and Tan (2005).

The second category focuses on studies that use indexes to forecast emerging markets. Studies from ex-Eastern Europe include Zorin and Borisov (2002) for the Latvian Riga stock exchange index, Walczak (1999), Wikowska (1995) for the Polish stock exchange index. Egeli, Ozturan, and Badur (2003), Yumlu, Gurgen, and Okay (2004, 2005) forecast the Istanbul Stock Exchange market. From Western European emerging markets, studies include Koulouriotis Koulouriotis (2004, 2001, 2002, 2005) for the Athens stock exchange, Andreou, Neocleous, Schizas, and Toumpouris (2000), Constantinou, Georgiades, Kazandjian, and Kouretas (2006) for the Cyprus stock exchange. The Singapore stock exchange is the most popular emerging market, forecasted by Ayob, Nasrudin, Omar, and Surip (2001), Hui, Yap, and Prakash (2000), Kim (1998), Phua, Hoh, Daohua, and Weiding (2001).

The third category includes articles that do not focus on a particular stock exchange market index, but use independent stocks or portfolio of stocks, instead. A typical example of this category is the study by Pantazopoulos, Tsoukalas, Bourbakis, Bruen, and Houstis (1998) that uses as input the price of the IBM stock, the study of Steiner and Wittkemper (1997), who selected as inputs the 16 top/bottom stocks from the DAX and the research by Atsalakis and Valavanis (2006a, 2006b) applied to five stocks of the Athens Stock Exchange and the NYSE.

3. Input variables

The number of input variables used in each model differs. In general, the average number of input variables is between four and ten; however, there are cases where only two input variables are used (Constantinou et al., 2006; Ettes, 2000). On the contrary, Olson and Mossman (2003), Zorin and Borisov (2002) use 59 and 61input variables, respectively.

Table 1
List of surveyed stock markets

Stock market	Article
Amsterdam exchange	Ettes (2000) and Setnes and Van Drempt (1999)
Athens stock exchange	Atsalakis and Valavanis (2006a, 2006b) and Koulouriotis et al. (2002, 2005)
Australian stock exchange	Barnes et al. (2000), Pan et al. (2005) and Vanstone et al. (2005)
Belgian stock market	Lendasse et al. (2000)
Cyprus stock exchange	Andreou et al. (2000) and Constantinou et al. (2006)
Financial times index	Brownstone (1996) and Kanas and Yannopoulos (2001)
German stock exchange	Schumann and Lohrbach (1993), Siekmann et al. (1999), Steiner and Wittkemper (1997), Wittkemper and Steiner (1996) and Rast (1999)
Hong Kong stock exchange	Lam (2001)
Indonesia stock exchange	Situngkir and Surya (2003)
Istanbul stock exchange	Egeli et al. (2003) and Yumlu et al. (2004, 2005)
Korean stock exchange	Baek and Cho (2002), Chun and Park (2005), Kim (1998), Kim and Han (1998) and Oh and Kim (2002)
Madrid stock exchange	Fernandez-Rodriguez et al. (2000) and Perez-Rodriguez et al. (2004)
NASDAQ	Ajith et al. (2003a, 2003b), Chen et al. (2005a) and Chen, Dong and Zhao (2005b)
New York stock exchange	Chaturvedi and Chandra (2004), Halliday (2004), Leigh et al. (2002) and Atsalakis and Valavanis (2006a, 2006b),
NIKKEI –Tokyo stock exchange	Huang et al. (2005), Jaruszewicz and Mandziuk (2004), Baba and Suto (2000), Mizuno et al. (1998) and Kimoto et al. (1990)
Philippine stock market	Bautista (2001)
Polish stock market	Walczak (1999) and Wikowska (1995)
Riga stock exchange	Zorin and Borisov (2002)
Sao Paolo stock exchange	Raposo et al. (2002)
Shanghais stock market	Cao et al. (2005), Yiwen et al. (2000), Zhang et al. (2004) and Zhongxing and Liting (1993)
Singapore stock exchange	Phua et al. (2001), Kim (1998), Hui et al. (2000) and Ayob et al. (2001)
Standard and Poor's 500 Index, NASDAQ and Dow Jones industrial average index	Ajith et al. (2003a, 2003b), Armano et al. (2004), Atiya et al. (1997), Casas (2001), Chen et al. (2005a, 2005b), Chenoweth and Obradovic (1996), Donaldson and Kamstra (1999), Grudnitski and Osburn (1993), Malliaris and Salchenberger (1993), Qi (1999), Pantazopoulos et al. (1998), Rech (2002), Thawornwong and Enke (2004), Tsaih et al. (1998), Wu et al. (2001), Kanas and Yannopoulos (2001) and Rech (2002)
Taiwan stock exchange	Chen et al. (2005b), Kuo (1998), Wang (2002) and Wang and Leu (1996)
Toronto stock exchange	Olson and Mossman (2003)

Table 2
Input variable choices

Article	Input variables
Ajith et al. (2003a)	Eight input variables (NASDAQ and 7 indexes)
Ajith et al. (2003b)	Opening, lowest, highest and closing index price
Andreou et al. (2000)	Index values of five previous days
Armano et al. (2004)	Ten variables (five Technical Analysis factors, price of last 5 days)
Atiya et al. (1997)	Eight fundamental analysis indicators
Atsalakis and Valavanis (2006a)	Change of stock prices in last two sessions
Atsalakis and Valavanis (2006b)	Three technical analysis indexes
Ayob et al. (2001)	Volume, opening, lowest, highest and closing index price
Baba and Kozaki (1992)	Fifteen technical analysis factors
Baba and Suto (2000)	Changes in stock prices
Baek and Cho (2002)	Volume ratio, relative strength index, rate of change, slow %D
Barnes et al. (2000)	Daily closing value
Bautista (2001)	Technical Analysis variables
Brownstone (1996)	FTSE index, exchange rate, interest rate, futures market etc
Cao et al. (2005)	Beta, cap, b/m
Casas (2001)	Seven economical indicators
Chandra and Reeb (1999)	Index values
Chaturvedi and Chandra (2004)	Three scaled input stock values
Chen et al. (2003)	TB, GCP12, GNP12, GDP12, CPI12, IP12
Chen et al. (2005a, 2005b)	Opening, highest and closing index price
Chenoweth and Obradovic (1996)	Six economical indicators
Chun and Park (2005)	Volume, opening, lowest, highest and closing index price
Constantinou et al. (2006)	Two lagged stock index returns
Doesken et al. (2005)	Five inputs depending on close, open, high values
Donaldson and Kamstra (1999)	Daily AR(1) stock return
Dong and Zhou (2002)	Eight technical patterns
Dong et al. (2003)	Five Technical Analysis variables
Dourra and Siy (2002)	Three technical indicators
Egeli et al. (2003)	Previous day's index values, TL/USD exchange rate, interest rate etc
Ettes (2000)	Two normalized volume price trend indicators from twenty stocks
Fernandez-Rodriguez et al. (2000)	The returns of the previous nine days
Gradojevic et al. (2002)	Lagged interest rate, lagged order flow
Grudnitski and Osburn (1993)	Three technical Analysis factors
Halliday (2004)	Daily index value
Harvey et al. (2000)	Total returns, price to earnings, price to book value, dividend yield
Huang et al. (2005)	S&P 500 index, USD/ Yen exchange rate
Hui et al. (2000)	Volume, lowest, highest and closing index price
Jaruszewicz and Mandziuk (2004)	Nineteen historical inputs, fourteen inputs from stock markets, eight Technical analysis factors
Kanas and Yannopoulos (2001)	Three technical analysis factors and a four regression variables
Kim (1998)	Stock price index, total return index, div. yield, vol., price/earnings ratio
Kim and Han (1998)	Technical analysis factors
Kimoto et al. (1990)	Vector curve, turnover, interest rate, foreign exchange rate, Dow Jones index
Kosaka et al. (1991)	Prices of three hundred stocks
Koulouriotis (2004)	Stock trend, stock profit, market profit, supply, demand
Koulouriotis et al. (2005)	Market trend/prof., demand & supply, forces, P-days ahead price change
Kuo (1998)	Technical analysis factors
Lam (2001)	Twelve market indicators
Leigh et al. (2002)	Twenty two technical analysis factors
Lendasse et al. (2000)	Twenty five technical analysis variables
Malliaris and Salchenberger (1993)	Exer., days, close price, volume, int., lag close price, lag mark. price
Mizuno et al. (1998)	Eleven technical indicators of TOPIX
Motiwalla and Wahab (2000)	Twenty technical analysis variables
Nishina and Hagiwara (1997)	Ten input of daily data
Olson and Mossman (2003)	Sixty one accounting and financial ratios
Pai and Lin (2005)	Daily stock data
Pan et al. (2005)	Last six daily closing prices
Pantazopoulos et al. (1998)	Daily closing value of index
Perez-Rodriguez et al. (2004)	Daily stock data
Phua et al. (2001)	Volume, opening, lowest, hhighest and closing index price, Dow Jones index value, NASDAQ index value, HIS index value, NIKKEI index value
Qi (1999)	Nine financial and economic variables
Quah and Srinivasan (1999)	Economical, political and firm/stock specific factors
Raposo et al. (2002)	Five fundamental analysis indicators
Rast (1999)	Daily closing price of index
Rech (2002)	Daily closing price of index
Refenes et al. (1993)	Three Technical Analysis factors
Safer and Wilamowski (1999)	Four price ratio averages, four volume ratio averages, one previous SUE
Schumann and Lohrbach (1993)	Thirteen economic time series
Setnes and Van Drempt (1999)	AEX price and macroeconomic factors
Schumann and Lohrbach (1993)	Shortrate, USD, DJ, Bonds, MSeuro
Simutis (2000)	Price error fact., exp. opin., gen. mark. dir., stock pr. mov. dir.
Steiner and Wittkemper (1997)	Six Technical Analysis variables
Tabrizi et al. (2000)	Gold coin average, USD exchange rate, volume, moving average of TSE for one and two Weeks
Tan et al. (1995)	Closing price data
Tang et al. (2002)	Moving average of weekly stock data
Thammano (1999)	Closing rates of the stock at four different lags
Thawornwong and Enke (2004)	Thirty one financial and economic variables
Tsaih et al. (1998)	Ten Technical Analysis factors
Walczak (1999)	Variables depending on the closing value
Wang (2002)	Stock price values collected periodically through the day
Wang and Leu (1996)	Daily stock value
Wikowska (1995)	BRE, KAB, volume, USD exchange rate
Wittkemper and Steiner (1996)	Daily stock data and yearly financial data
Wong et al. (1992)	Eleven Technical Analysis factors
Wu et al. (2001)	Previous S& P500 values and six economical indices
Yiwen et al. (2000)	Six economical variables
Yumlu et al. (2004)	ISE index XU100
Yumlu et al. (2005)	ISE index previous data
Zhang et al. (2002)	Opening, lowest, highest and closing index price
Zhang et al. (2004)	Closing index price
Zhongxing and Liting (1993)	Raw daily data
Zorin and Borisov (2002)	Dow Jones Riga stock exchange

Table 3
Summary of modeling techniques

Article	Data preprocessing	Sample size	Type (transfer functions for ANNs)	Network layers	Membership functions	Validation set	Training method
Ajith et al. (2003a)	PCA	D:24months	FFNN	8/20/20/1	–	20%	SCGA
Ajith et al. (2003b)	–	D:4.7years	FFNN (tanh–sig)	4/26/1	–	–	Lev–Mar Alg
Andreou et al. (2000)	No	718	FFNN (log,tanh)	–	–	35	EBP
Armano et al. (2004)	Log	2160	NXCS	–	–	200	EBP
Atsalakis and Valavanis (2006a)	Yes	4500	ANFIS	5	gbell	60	EBP
Atsalakis and Valavanis (2006a)	Yes	4850	ANFIS	5	gauss	60	EBP
Ayob et al. (2001)	Yes	1478	FFNN (sig)	–	–	–	EBP
Baba and Kozaki (1992)	–	20	NN	15/–/–/1	–	–	EBP,RanOpt
Baba and Suto (2000)	–	D:60months	NN+TDL Method	14/50/2	–	–	EBP,RanOpt
Baek and Cho (2002)	–	D:28months	AANN (tan sig)	–	–	–	Lev–Mar Alg
Barnes et al. (2000)	No	250	BPN	1/1–8/1	–	–	PRW
Bautista (2001)	[−1,1]	720	FFNN	–	–	52	Lev–Mar Alg
Brownstone (1996)	[0,1]	1800	BPN	54/–/1	–	No	FIX
Cao et al. (2005)	–	D:4years	FFNN	–	–	–	EBP
Casas (2001)	Yes	≈960	FFNN	6/2/3		Yes	MSE
Chandra and Reeb (1999)	–	D:300mont	BPN	–/–/1	–	No	FIX
Chaturvedi and Chandra (2004)	No	40	BPN	3/3/3	–	Yes	EBP
Chen et al. (2003)	–	≈2400	PNN	2/6/2/1		Yes	–
Chen et al. (2005a)	–	D: 5years	Fuzzy	–	–	–	PSO Alg
Chen et al. (2005b)	–	D: 5years	Wavelet NN	–	–	–	EDAs
Chenoweth and Obradovic (1996)	Yes	2273	Hybrid NN		–	1273	EBP
Chun and Park (2005)	Log	1099	Dyn.Adp.Learn.	C.B.R.	–	42	Sim. Anneal.
Constantinou et al. (2006)	Log	1444	MLP	2/8/1	–	–	–
Doesken et al. (2005)	Yes	–	Fuzzy FFNN	8/20/7/1	–	–	GA
Donaldson and Kamstra (1999)	–	D:18years	Hyb ANN	–	–	–	–
Dong and Zhou (2002)	Yes	44,150	Fuzzy	–	Trapezoid	–	–
Dong et al. (2003)	Yes	68,933	FFNN	5/40/1	–	–	–
Dourra and Siy (2002)	[0,1]	D:2years	Fuzzy	–	Bell	–	–
Egeli et al. (2003)	–	417	MLP/ FFNN	Various	–	10%	EBP
Ettes (2000)	Yes	D:8years	Fuzzy	–	–	2 last	GA
Fernandez-Rodriguez et al. (2000)	–	6931	FFNN	–	–		EBP
Gradojevic et al. (2002)	–	1846	NF	–	Gaus,Bell, Triangular	23	–
Grudnitski and Osburn (1993)	–	D:94months	NN	–	–		–
Halliday (2004)	Log	D:15years	FFNN,Elman NN	2/3,5,10/1	–	–	EBP
Harvey et al. (2000)	–	–	NN	–	–	Yes	EBP
Huang et al. (2005)	Log	676	SVM	–	–	36	SVM
Hui et al. (2000)	[0,1]	D:10years	Hyb MLP (sig)	4/20/15/1	–	–	Sliding Wind
Jaruszewicz and Mandziuk (2004)	[−1,1]	4399	MLP	–	–	No	EBP
Kanas and Yannopoulos (2001)	[Log]	D:21years	MLP (log)	3/6/1	–	Yes	EBP
Kim (1998)	Yes	3056	PNN		–	186	EBP
Kim and Han (1998)	No	750	Hyb. ANN (sig)	–	–	150	EBP
Kimoto et al. (1990)	[0,1]	D:56months	NN	–	–	Yes	Sup. Learn.
Kosaka et al. (1991)	–	≈1200	BPN	–	–	–	EBP
Koulouriotis (2004)	–	D:10months	FCM	–	Sigmoid	Yes	Evolution Str.
Koulouriotis et al. (2002)	–	330	FCM	–	–	–	ES–bas. Alg.
Koulouriotis et al. (2005)	–	200	FFNN (tan sig)	–	–	Yes	Lev–Mar Alg, Evol. Strat.
Kuo (1998)	[0,1]	–	MLP	42/60/60/1	–	–	EBP
Lam (2001)	No	D:2years	FUZZY	–	–	–	G.A.
Leigh et al. (2002)	Zscore	3840	BPNN	22/8/2	–	250	EBP
Lendasse et al. (2000)	–	2600	RBFNN	–	–	–	MW
Malliaris and Salchenberger (1993)	[0,1]	280	FFNN (sigmoid)	–	–	Yes	EBP
Mizuno et al. (1998)	Yes	D:95months	NN	–	–	119	Equal. Learn.
Motiwalla and Wahab (2000)	–	D:99months	NN	20/9/11	–	Yes	EBP
Nishina and Hagiwara (1997)	–	–	NF	–	–	–	LMS
Oh and Kim (2002)	–	3069	BPNN	–	–	Yes	–
Olson and Mossman (2003)	[−1,1]	2352	BPN (hyp.)	–	–	Yes	DRLA
Pai and Lin (2005)	–	50	Hyb. ARIMA, SVM	–	–	Yes	–
Pan et al. (2005)	–	D: 12.5year	MLP	–	–	20%	–
Pantazopoulos et al. (1998)	Yes	≈15,600	FFNN NF	–	Triangular	6000 last	Reliability index
Perez-Rodriguez et al. (2004)	log	2520	MLP (hyp tan)	–	–	–	Cross–Valid.
Phua et al. (2001)	–	360	FFNN	–	–	–	EBP
Qi (1999)	–	468	RNN	–	–	–	–
Quah and Srinivasan (1999)	–	D:4years	BPN	7/4,8,14/1	–	Yes	EBP
Raposo et al. (2002)	–	153	FFNF	–	–	Yes	–
Rast (1999)	–	500	MLP NF	4/5/1	–	Yes	Quick prop.
Rech (2002)	log	1076	ANN	–	–	480	–
Refenes et al. (1993)	–	10,260	FFNN	3/32/16/1	–	–	EBP
Safer and Wilamowski (1999)	–	–	FFNN (sig)	9/5/1	–	20%	Lev–Mar Alg
Schumann and Lohrbach (1993)	–	D: 9years	CDN	13/–/–/4	–	–	EBP
Setnes and Van Drempt (1999)	–	–				–	MW
(Siekmann et al., 1999)	–	–	NF	1/2/1	Gausian, Logistic	–	–
Simutis (2000)	Yes	D:24months	Fuzzy	–	Gausian–Bell	–	–

(*continued on next page*)

Table 3 (*continued*)

Article	Data preprocessing	Sample size	Type (transfer functions for ANNs)	Network layers	Membership functions	Validation set	Training method
Situngkir and Surya (2003)	–	–	MLP	–	–	–	EBP
Steiner and Wittkemper (1997)	–	≈672	GRNN	–	–	Yes	–
Tabrizi et al. (2000)	log	≈240	MLP	8/3/1	–	Yes	EBP
Tan et al. (1995)	Yes	D: 6.6years	PNN	–	–	–	–
Tang et al. (2002)	–	–	NF	–	–	–	EBP
Thammano (1999)	–	D:38months	NF	7/–/1	–	–	Fuzzy system
Thawornwong and Enke (2004)	–	D:24years	FFNN (sigmoid)	10–16/14-27/2		Yes	EBP
Tsaih et al. (1998)	–	D:9years	Hybrid Reas.NN	–	–	4Y	–
Vanstone et al. (2005)	–	–	NN	–	–	–	–
Versace et al. (2004)	Yes	D: 320	RBPN/RBFN, GA		–	63	G.A.
Wah and Qian (2002)	Yes	D:60months	RFIR ANN	–	–	Yes	EBP
Walczak (1999)	Yes	≈310	BPN	–/1–2/–	–	130	–
Wang (2002)	–	6,700	Fuzzy Grey Pred.	–	–	1680	–
Wang and Leu (1996)	Yes	D:4years	Hyb. ANN	–	–	3M	EBP
Wikowska (1995)	No	≈25	BPN	3–5/2–3/1,3	–	Yes	MSE
Wittkemper and Steiner (1996)	[0,1]	D:19years	NN + GA	–	–	–	MSE
Wong et al. (1992)	–	D:2years	BPN + Fuzzy	–	–	–	DLRA
Wu et al. (2001)	–	–	FFNF NF	9/–/1	–	Yes	–
Yiwen et al. (2000)	–	–	BPN	6/10/1	–	–	–
Yumlu et al. (2004)	Yes	3650	RNN	–	–	985	MSE
Yumlu et al. (2005)	Yes	2946	RNN	7/20/–	–	Yes	MSE
Zhang et al. (2002)	–	–	FFNN	–	–	Yes	HLN
Zhang et al. (2004)	[0.1, 0.9]	500	BPN	–	–	–	EBP
Zhongxing and Liting (1993)	[0,1]	–	FFNN w fuzzy	–	–	–	BP
Zorin and Borisov (2002)	[−1,1]	273	BPN (sig, hyp.tan)	59/35/1	–	20	EBP

" –": Not mentioned in the article.

Specific techniques are also utilized to choose the most important input variables for the forecasting process among a large number of candidate ones, based on how each input affects obtained results. Some studies cover a large horizon of observations over a period of years. The mean value or the latest observed value of a stock is used to fill any missing observations.

The most commonly used inputs are the stock index opening or closing price, as well as the daily highest and lowest values, supporting the statement that soft computing methods use quite simple input data to provide predictions.

About 30% of the surveyed articles use as input data stock or index prices, that is, the daily closing price or some indicator depending only on it, as in Barnes et al. (2000), Donaldson and Kamstra (1999), Halliday (2004), Tan, Prokhorov, and Wunsch (1995), Pai and Lin (2005), Pantazopoulos et al. (1998), Perez-Rodriguez et al. (2004), Rast (1999), Rech (2002), Walczak (1999), Wang and Leu (1996), Zhang et al. (2004) and Zhongxing and Liting (1993). The daily opening/closing price, the daily minimum/ maximum price and, in some cases, the transactions volume are used by Ajith et al. (2003a), Ayob et al. (2001), Chandra and Reeb (1999), Chen et al. (2005a), Chun and Park (2005), Doesken, Abraham, Thomas, and Paprzycki (2005), Thammano (1999), Wang (2002) and Zhang et al. (2002). In addition, the daily closing price is used in combination with the closing price of previous days (usually up to a week) by Andreou et al. (2000), Fernandez-Rodriguez et al. (2000), Pan et al. (2005), Tang, Xu, Wan, and Zhang (2002) and Atsalakis and Valavanis (2006b).

Studies that use daily data combined with closing prices of established markets like the Dow Jones, the S&P, or with exchange rates of strong currencies like USD, EURO, YEN include, Ajith et al. (2003a) who uses besides the main Stock Index that it forecasts another 7 indexes closing prices; Huang et al. (2005) who uses the S&P 500 and the USD/YEN exchange rate to forecast the NIKKEY index; the study from Phua et al. (2001) who uses the DJ, NASDAQ, HIS and NIKKEY index values to forecast the Singapore stock exchange; the study by Siekmann et al. (1999) who uses the DJ index values as well as the USD and EURO exchange rate, the study by Tabrizi et al. (2000) who forecasts the Tehran Stock exchange using Gold Coin value and the USD exchange rate; the study by Wikowska (1995) who uses the USD exchange rate to forecast the Polish stock index. In general, well established stock index values and exchange rates are used by researchers who try to forecast emerging markets. That indicates that emerging markets are greatly influenced compared to well established markets.

About 20% of the surveyed articles use as inputs technical analysis factors that are sometimes combined with daily or previous stock index prices, as in Armano et al. (2004) and Atsalakis and Valavanis (2006b). The technical analysis factors range from 2 to 25, with most articles using mostly a combination of all previously described variables, and also fundamental analysis indicators and statistical data. An extreme case is reported in Kosaka, Mizuno, Sasaki, Someya, and Hamada (1991) who uses as input 300 stock prices! Table 2 summarizes input variable choices.

4. Forecasting methodology

Each surveyed paper is classified with respect to data preprocessing, sample size, type of implemented technique and its characteristics (number of ANN layers or fuzzy set membership functions), validation data sets and training method.

Input data preprocessing and proper sampling may impact forecasting performance. Choice of indicators as inputs through sensitivity analysis may help eliminate redundant inputs. In many cases input data has a large range of values reducing effectiveness of training procedures. This may be overcome by data normalization. Data normalization techniques include logarithmic data preprocessing (9 studies), and scaling of data between ranges of 0 and 1 or −1 and 1 (13 studies). Additional techniques used for preprocessing are the Principal Component Analysis (PCA) used by Ajith et al. (2003a), the Z score used by Leigh et al. (2002) and an ANFIS technique used by Atsalakis and Valavanis (2006a). It is stated that not all articles provide details about data preprocessing, or whether any preprocessing occurs. However, an important observation is that almost all articles referring to data preprocessing find it useful and necessary.

Table 4
Comparative studies

Article	ANNs	LR, MLR	ARMA, ARIMA	GA	RW	B & H	Others
Andreou et al. (2000)	•						•
Armano et al. (2004)	•					•	
Atsalakis and Valavanis (2006a)						•	
Atsalakis and Valavanis (2006b)						•	
Baba and Kozaki (1992)							
Baek and Cho (2002)						•	
Barnes et al. (2000)		•	•				•
Bautista (2001)					•		
Brownstone (1996)		•					
Cao et al. (2005)		•					•
Casas (2001)						•	
Chandra and Reeb (1999)						•	
Chaturvedi and Chandra (2004)		•					
Chen et al. (2003)					•	•	
Chen et al. (2005a, 2005b)	•						
Chenoweth and Obradovic (1996)	•					•	
Chun and Park (2005)					•		
Doesken et al. (2005)						•	
Donaldson and Kamstra (1999)			•				•
Dong et al. (2003)		•					
Dourra and Siy (2002)							•
Egeli et al. (2003)	•						
Fernandez-Rodriguez et al. (2000)					•	•	
Harvey et al. (2000)		•				•	
Huang et al. (2005)	•						•
Hui et al. (2000)	•						
Kanas and Yannopoulos (2001)		•					
Kim (1998)	•						
Kim and Han (1998)						•	•
Kimoto et al. (1990)		•					
Kosaka et al. (1991)							•
Koulouriotis (2004)							•
Koulouriotis et al. (2001)						•	
Koulouriotis et al. (2002)		•					
Koulouriotis et al. (2005)	•	•					•
Lam (2001)						•	
Leigh et al. (2002)						•	
Malliaris and Salchenberger (1993)							
Mizuno et al. (1998)	•						•
Motiwalla and Wahab (2000)		•				•	
Nishina and Hagiwara (1997)	•						
Oh and Kim (2002)	•					•	
Olson and Mossman (2003)	•						
Pai and Lin (2005)			•				•
Pan et al. (2005)							•
Pantazopoulos et al. (1998)							•
Phua et al. (2001)							
Qi (1999)		•					
Quah and Srinivasan (1999)							•
Raposo et al. (2002)	•						•
Rast (1999)	•						
Rech (2002)			•				•
Refenes et al. (1993)		•					
Schumann and Lohrbach (1993)			•				
Setnes and Van Drempt (1999)		•				•	
(Siekmann et al., 1999)		•			•	•	•
Steiner and Wittkemper (1997)							
Thammano (1999)	•						
Thawornwong and Enke (2004)	•	•				•	•
Tsaih et al. (1998)						•	
Vanstone et al. (2005)						•	
Wah and Qian (2002)	•		•				•
Walczak (1999)							
Wang and Leu (1996)		•					
Wikowska (1995)							
Wittkemper and Steiner (1996)		•		•			•
Wu et al. (2001)	•						
Yumlu et al. (2004)	•						•
Yumlu et al. (2005)	•						
Zhang et al. (2002)	•						
Zhang et al. (2004)						•	
Zorin and Borisov (2002)	•		•				•

The sample size chosen by most authors is daily data with only a few cases of missing values. This is because there is no guarantee that if longer periods of data are used as inputs, better results will be obtained. Representative studies include Chaturvedi and Chandra (2004) who uses only 40 observations, Koulouriotis et al. (2005) who uses 2000 observations, Thawornwong and Enke (2004) who uses 24 years of data, Kanas and Yannopoulos (2001) who uses 21 years of data and Atsalakis and Valavanis (2006a) who uses 18 years of daily data. Regardless, when trying to forecast a well established stock index, a large amount of data is required due to the fact that the direction of stock market indexes changes in the long run.

The specific methods/ techniques used to develop forecasting models are listed in Table 3. This Table is probably the most important aspect of this study since it classifies techniques used to forecast subject stock markets. Overall, implemented techniques focus on neural networks and neuro-fuzzy approaches; fuzzy cognitive maps (FCM) that are directed graphs with concepts like values, events, as nodes and causalities as edges Koulouriotis, 2004; Koulouriotis et al., 2001 and Koulouriotis et al., 2002; Support Vector Machines (SVM) that are learning machines performing binary classification and real valued function approximation tasks (Huang et al., 2005).

About 60% of the surveyed articles use feed forward neural networks (FFNN) and recurrent networks. Studies that utilize neural networks include Constantinou et al. (2006) who uses a MLP Network with 2 inputs, Motiwalla and Wahab (2000), who uses a back propagation neural network and Refenes, Azeme-Barac, and Zapranis (1993) who utilizes a feed forward network with 4 layers (two hidden ones). Two special cases are probabilistic neural networks (PNN), a standardized architecture neural network used by Kim and Han (1998) and the radial basis function network (RBFN) that has two layers and it is a special class of multilayer feed-forward networks; each unit in the hidden layer employs a radial basis function, such as a Gaussian kernel, as the activation function.

Neuro-fuzzy networks are also widely used, which combine structural and learning capabilities of neural networks with linguistic initialization and validation aspects of fuzzy systems. Neuro-fuzzy systems are categorized based on the type of membership functions employed, the most common ones being the Gaussian, the sigmoid and the G-bell. When regarding fuzzy systems as types of neural networks, the role of membership functions in determining decision surfaces forms is highlighted instead of accuracies in modeling vagueness or uncertainty associated with particular linguistic terms. The rule-based representation of neuro-fuzzy systems offers transparency as demonstrated by Atsalakis and Valavanis (2006a).

The average number of hidden layers is one or two. Regarding input nodes the maximum number is 42 used by Kuo (1998) and 52 used by Zorin and Borisov (2002).

Table 5
Summary of performance measures

Article	Model performance measures
Ajith et al. (2003a)	RMSE, HIT
Andreou et al. (2000)	CC, MAE, HIT
Armano et al. (2004)	HIT, PROFIT
Atsalakis and Valavanis (2006a)	HIT, RMSE, MAE, MAPE
Atsalakis and Valavanis (2006b)	HIT, RMSE, MAE, MAPE
Baba and Kozaki (1992)	Total relative error
Baek and Cho (2002)	FAR, FRR
Bautista (2001)	MSPE, HIT, Diebold-Mariano statistic
Brownstone (1996)	MSE, RMSE
Cao et al. (2005)	MAD, MAPE, MSE, SD, Diebold-Mariano
Casas (2001)	MSE
Chandra and Reeb (1999)	RETURN
Chaturvedi and Chandra (2004)	R^2
Chen et al. (2005a, 2005b)	MAP, MAPE, CC, RMSE
Chenoweth and Obradovic (1996)	AAR, BETC
Chun and Park (2005)	MAPE, HIT, *t*-Value
Doesken et al. (2005)	MSE, NMSE, HIT, RETURN
Donaldson and Kamstra (1999)	Graphical Comparison of results
Dong and Zhou (2002)	MAR, CAR
Dong et al. (2003)	ECM cost function
Dourra and Siy (2002)	HIT, PROFIT
Egeli et al. (2003)	MAPE,MSE, R^2
Fernandez-Rodriguez et al. (2000)	RETURN
Grudnitski and Osburn (1993)	HIT
Halliday (2004)	HIT, APE, STANDARD DEVIATION
Harvey et al. (2000)	RETURN, HIT, %Modified direction
Huang et al. (2005)	Covariance Matrice
Hui et al. (2000)	RETURN
Jaruszewicz and Mandziuk (2004)	APE
Kanas and Yannopoulos (2001)	RMSE, *P*-value
Kim (1998)	HIT, McNemar Test
Koulouriotis (2004)	HIT, In sample error
Koulouriotis et al. (2001)	HIT, %PROFIT
Koulouriotis et al. (2005)	HIT, MSE
Kuo (1998)	MSE, PROFIT, other financial measures.
Lam (2001)	Genetic algorithm
Leigh et al. (2002)	HIT, *t*-Test
Lendasse et al. (2000)	HIT
Malliaris and Salchenberger (1993)	MAD, MAPE, MSE
Mizuno et al. (1998)	HIT
Motiwalla and Wahab (2000)	Eleven statistical indices for direct accuracy
Oh and Kim (2002)	APE, RMSE, MAE
Olson and Mossman (2003)	HIT, RETURN
Pai and Lin (2005)	MSE
Pan et al. (2005)	RMSE, VR, HIT
Pantazopoulos et al. (1998)	RMSE, HIT
Qi (1999)	RMSE, MAE, MAPE, PCC
Quah and Srinivasan (1999)	HIT
Raposo et al. (2002)	HIT
Rast (1999)	HIT
Rech (2002)	RMSE, MAE, Diebold-Mariano Statistic
Refenes et al. (1993)	RMSE, POCID, DIRECTION
Safer and Wilamowski (1999)	MSE
Schumann and Lohrbach (1993)	HIT
Setnes and Van Drempt (1999)	RMSE, SIGN%, WEALTH%
(Siekmann et al., 1999)	HIT, RMSE, PROFIT
Situngkir and Surya (2003)	Auto correlation
Steiner and Wittkemper (1997)	RETURN
Tabrizi et al. (2000)	NMSE, learning rate
Tan et al. (1995)	HIT, *r*, false alarm rate
Thawornwong and Enke (2004)	RMSE
Tsaih et al. (1998)	HIT
Vanstone et al. (2005)	Return. SD, PROFIT, DOF, Zscore
Versace et al. (2004)	*t*-test, x^2-test
Wah and Qian (2002)	HIT, MSE
Wikowska (1995)	MSE
Wittkemper and Steiner (1996)	MSE
Wu et al. (2001)	HIT
Yumlu et al. (2004)	MSE, HIT, TIC, correlation
Yumlu et al. (2005)	MAE, RMSE, correlation
Zhang et al. (2004)	HIT
Zorin and Borisov (2002)	RMSE

Table 4 shown below is related to Table 3. In reality, Table 4 enhances information provided in Table 3 by stating which authors compare their derived benchmark models against other models.

5. Performance measures

Table 5 presents the list of performance measures used to evaluate each author's approach. Utilized performance measures may be classified as statistical measures and as non-statistical measures.

Statistical measures include the root mean square error (RMSE), the mean absolute error (MAE) and the mean squared prediction error (MSPE), statistical indicators like the autocorrelation, the correlation coefficient, the mean absolute deviation, the squared correlation and the standard deviation. Bautista (2001), Cao et al. (2005), Rech (2002) use the Diebold Mariano test that calculates a measure of predictive accuracy. Akaike's minimum final prediction error (FPE) is used as a performance measure by Chen et al. (2003). The Theil Inequality coefficient is used by Yumlu et al. (2004) as a measure of the degree to which one time series differs from another.

Non-statistical performance measures include measures that are related with the economical side of the forecast. The most common used performance measure is the so called Hit Rate that measures the percentage of correct predictions of the model. Another two measures that deal with the profitability of the model are the annual rate of return and the average annual profit of the model.

6. Conclusions

This study has surveyed articles that have applied neural networks and neuro-fuzzy models to predict stock market values. The study has focused on input data, forecasting methodology, model comparisons and measures used for performance evaluation.

The observation is that neural networks and neuro-fuzzy models are suitable for stock market forecasting. Experiments demonstrate that soft computing techniques outperform conventional models in most cases. They return better results as trading systems and higher forecasting accuracy.

However, difficulties arise when defining the structure of the model (the hidden layers the neurons etc.). For the time being, the structure of the model is a matter of trial and error procedures.

Appendix. Data preprocessing

Yes	Data preprocessing is made, but the author dos not give any further details
No	No data preprocessing is made
$[\alpha,\beta]$	Data preprocessing is made by transforming the initial data in the interval of $[\alpha, \beta]$
Log	A logarithmic data transformation is made

Sample size

α	Size of daily observations made
$\approx\alpha$	Estimated size of daily observations made
D: αYears	Sample size is taken in daily basis during a period of α years
D: αMonths	Sample size is taken in daily basis during a period of α months
D: αWeeks	Sample size is taken in daily basis during a period of α weeks

Type

The type of the methodology used is described:

ANN Artificial neural network
BPN Backpropagation neural network
FBPN Backpropagation neural network with fuzzy rules
FCM Fuzzy cognitive maps
FFNN Feedforward neural network
FFNF Feedforward neural network with fuzzy rules
Fuzzy Fuzzy logic based system
GA Genetic algorithm
GRNN General regression neural network
Hyb ANN Hybrid artificial neural network
MLP Multilayer perceptron
MLPF Multilayer perceptron with fuzzy rules
NF Neuro-fuzzy
TDLM Temporal difference learning method
NXCS Hybrid system that integrates extended classifier system with Genetic Algorithms and ANNs
PNN Probabilistic neural network
RBFN Radial basis function neural network
RBPN Recurrent backpropagation neural network
RFIR Recurrent FIR neural network
RNN Recurrent neural network
SVM Support vector machines
TDRNN

Network layers

In case of neural and neuro-fuzzy approaches, the number of layers is mentioned in the following way:$\alpha/x/\ldots/x/\beta$, where α, number of input neurons; β, number of output neurons; x, number of hidden neurons in each hidden layer. The number of hidden layers equals to the times that x appears. For example 4/5/5/2 refers to two hidden layers with 5 neurons in each

Membership functions

In case of Neuro-fuzzy and fuzzy approaches, the membership function used is referred.

Bell Generalized bell-shaped membership function.
Gausian–Bell Gaussian curve membership function.
Logistic Logistic membership function.
Sigmoid Sigmoid shaped membership function.
Trapezoid Trapezoidal-shaped membership function.
Triangular Triangular membership function.

Validation set

Yes Validation set exists but the author does not mention anything further.
No The author does not use validation set
α% The α percent of the sample size is used for validating the results of the model.
α α Data observations were used as validation set.
α Last The last α observations were used as validation set.

Training method

The method used for the training if the model is referred:

SCGA Sealed conjugate gradient algorithm
EBP Error backpropagation
EBP,RanOpt Error backpropagation combined with random optimization method
EDAs Estimation of distribution algorithms
Cross-Vali. Cross-validation method
DRLA Delta rule learning algorithm
Equal.Learn. Equalized learning training method
Evolution Str. Evolution strategies method training
Fix. Sample Fixed sample training
FuzzySystem Training with fuzzy system
G.A. Training with genetic algorithm
HLN Heuristic knowledge based learning algorithm
Lev-Mar Alg Lavenberg–Marquardt optimization algorithm.
LMS Least mean square training
MSE Minimization of the mean square error (MSE)
MW Moving window
PRW Pattern recognition workbench
PSO Alg Particle swarm optimization algorithm
Quickprop QuickProp training algorithm
Sim. Anneal. Simulated annealing training technique
Sliding Wind Sliding window training
Sup. Learn. Supplementary learning
SVM Support vector machines

Modeling benchmarks

ANNs The results of the model are compared to those obtained using similar artificial neural network models.
LR/ MLR The results of the model are compared to those obtained using linear regression and multi-linear regression.
ARMA/ ARIMA The results of the model are compared to those obtained using autoregressive – moving average models.
GA The results of the model are compared to those obtained using genetic algorithms.
RW The results of the model are compared to those obtained using the Random Walk model.
B & H The results of the model are compared to those obtained using the Buy and Hold trading strategy.
Others The results of the model are compared to those obtained using other forecasting techniques.

Performance measures

AAR Annual rate of return
AC Autocorrelation
APE Average percentage error
BETC Break even transaction cost
CAR Cumulative abnormal return
CC Correlation coefficient
DOF Degrees of freedom
FAR False acceptance rate
FRR False rejection rate
FPE Akaike's minimum final prediction error
HIT Hit rate
MAD Mean absolute deviation
MAE Mean absolute error
MAP Maximum absolute percentage error
MAPE Mean absolute percentage error
MAR Mean abnormal return
MSE Mean squared error
MSPE Mean squared prediction error
NMSE Normalized mean square error
PCC Pearson's correlation coefficient
POCID Percentage of change in direction
PROFIT Average annual profit of the model. (See also Table 5)
P-value *P*-value is a measure of how much evidence there is against the null hypothesis.
R^2 Squared correlation
RETURN Average annual returns of the model. (See also Table 5)
RMSE Root mean square error
SD Standard deviation (also referred as the Greek letter σ)

TIC Theil inequality coefficient
VR Variance reduction
σ Standard deviation.

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