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Soft Computing Techniques for Stock Market Prediction: A Literature Survey

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Abstract: Stock market trading is an unending investment exercise globally. It has potentials to generate high returns on investors' investment. However, it is characterized by high risk of investment hence, having knowledge and ability to predict stock price or market movement is invaluable to investors in the stock market. Over the years, several soft computing techniques have been used to analyze various stock markets to retrieve knowledge to guide investors on when to buy or sell. This paper surveys over 100 published articles that focus on the application of soft computing techniques to forecast stock markets. The aim of this paper is to present a coherent of information on various soft computing techniques employed for stock market prediction. This research work will enable researchers in this field to know the current trend as well as help to inform their future research efforts. From the surveyed articles, it is evident that researchers have firmly focused on the development of hybrid prediction models and substantial work has also been done on the use of social media data for stock market prediction. It is also revealing that most studies have focused on the prediction of stock prices in emerging market.

Keywords: Stock market prediction, Soft computing, ANN, SVM, Hybrid prediction models.

1. Introduction

The stock market is a market in which company stocks and derivatives are traded at an agreed price; they are refer to securities listed on stock exchanges and those traded privately (Dase et al., 2010). Globally, the stock market has attracted a large number of investors and economists (Agrawal et al., 2013). This is because it has the opportunity of highest return over other schemes and is a key source of fund raising for companies through initial public offer (IPO) (Sureshkumar and Elango, 2012). As stated in (Chakravaty and Dash, 2012), several techniques have been employed for stock market prediction of which statistical methods have been extensively used. Some of the statistical techniques that have been used for stock market prediction include autoregressive conditional heteroscedasticity (ARCH), autoregressive integrated moving average (ARIMA), autoregressive moving average (ARMA) amongst others. However, these models can predict linear patterns only while the stock market returns change in a non-linear pattern (Vaisla and Bhatt, 2010). The stock market is dynamic, evolutionary, complex and non-linear in nature thus several non-linear approaches to stock market prediction such as generalized autoregressive conditional heteroskedasticity (GARCH) have been proposed (Liu et al., 2012). Forecasting of stock returns is difficult because of the need to capture market volatility to implement prediction models (Atsalakis &Valvanis, 2009).

Recently, a lot of research has been carried out to using various soft computing approaches for stock market price forecasting (Liu et al., 2012). Soft computing techniques offer useful tools in forecasting noisy environments and can capture their nonlinear behaviour (Atsalakis & Valvanis, 2009). This paper carries out a literature survey of 120 published articles that focus on the application of soft computing techniques for stock market prediction. The result of the review is presented in three summary tables. The first table presents a list of stock markets that each author modeled for prediction, summary of the objective of each article as well as the experimental data used in each study. The second table summarizes information about the modeling techniques employed in each reviewed article. The third table presents the models that were compared with each proposed prediction model, the performance measures employed for comparison and the result of the comparison.

This research cohesively presents information on the various soft computing techniques that have been employed to model and predict different stock markets. This paper would help researchers to know the current state of the art in stock market prediction, facilitate comparative studies as well as spot current research opportunities.

The remainder of this paper is organized as follows: A background of the research work and related works is presented in Section 2, in Section 3 a detailed description of the methodology employed for the research is presented as well as the various summary tables, discussion points are presented in Section 4 and Section 5 contains concluding remarks.

2. Related Work

Investment in the stock market is regarded as high risks and high gains as such investors and researchers alike have sought for tools and methods that would increase their gains as well as minimize their risks (Agrawal et al., 2013). Soft and evolutionary computing methods for stock price prediction have become hugely popular for accurate prediction of stock market behavior because of their ability to handle the uncertain, chaotic and non-linear nature of the stock market (Chakravaty et al., 2011).

In (Atsalakis et al., 2009) a survey of articles whose focus is on neural and neuro-fuzzy techniques for stock market predictions was carried out. Summary tables were presented in terms of input variable choices, comparative studies, modeling techniques, performance measures and surveyed stock markets. (Agrawal et al., 2013) studies stock prediction techniques applied to the Indian stock market and presents the advantages and disadvantages of the methods. Additionally, it presents a comprehensive review of the significant developments in the field of stock prediction of Indian stock market. (Dase&Pawar, 2010) presents a review of literature on the application Artificial Neural Network for stock price prediction. (Santosh et al., 2013) presents a literature review outlining the various application areas of soft computing techniques.(Sheng & Subhash 2012) discusses and presents various realms that can be predicted with social media. It then presents a discussion of the various prediction methods used with social media. (Wu et al., 2010) carried out a comparison study of 5 bankruptcy prediction models drawn from literature and then developed a model that aggregates the key variables from the models as well as adding a new variable. It is reported that the new model outperformed the existing models.

(Li & Ma, 2010) carried out a literature survey of the application of ANNs in a number of aspects of financial economics namely: stock price forecasting, option pricing, exchange rate forecasting and the prediction of banking and financial crisis. (Bahrammirzaee, 2010) carried out a comparative literature review of artificial intelligence applications in finance focusing on the application of ANNs, expert systems and hybrid intelligent systems in the areas of credit evaluation, portfolio management, financial prediction and planning. (Preethi & Santhi, 2012) carried out a literature survey of the use of ANN, Data mining, Hidden Markov Model and Neuro-Fuzzy systems for stock market fluctuation prediction. (Hajizadeh et al., 2010) carried out a literature survey of data mining techniques applied to data from various stock markets. (Nikfarjam et al., 2010) carried out a literature survey of research works that focused on the mining of text from financial news for stock price prediction. A presentation of the main components of text mining systems was made as well as how each component was implemented in the reviewed papers.

3. Methodology

To carry out this study, published articles that focused on the application of neural networks, neuro-fuzzy and other soft computing methods were reviewed. Articles that focused on the use of social media data with soft computing methods for stock market prediction were also reviewed. Results of the study are presented in three summary tables. The stock market surveyed, experimental data used, methodology employed and summary of the objective of each reviewed article is presented in table 1. Table 2 presents information of the modeling techniques employed in each reviewed article in terms of input variables, prediction model, training method, network layers, and data preprocessing. Table 3 presents the prediction models against which each article's prediction model was compared, the performance measures that formed the basis of evaluation, as well as the result of the comparison.

Table 1: Summary of the reviewed articles

Article	Market Surveyed	Experimental Data (Training Data)	Summary
Chakravarty et al., (2012)	S&P 500, DJIA Index, BSE	S&P, BSE, DJIA dataset	Proposes a hybrid model of integrated functional link interval type 2 fuzzy neural system (FLIT2NS) for stock price prediction
Fenghua et al., (2014)	Shanghai Stock Exchange	SSE data	proposes a hybrid model of Singular spectrum analysis and support vector machine for stock price prediction
Kara et al., (2011)	Instanbul Stock Exchange	ISE National 100 index dataset	Predicted direction of movement in the daily ISE National 100 index using ANN and SVM and compares the performances of the models
Hsieh et al., (2011)	TAIEX, DJIA	TAIEX,DJIA, Nikkei, FTSE dataset	Proposes a model that uses wavelength transforms and RNN based on ABC algorithm for stock price prediction
Sureshkumar et al., (2012)	National Stock Exchange	NSE Dataset	
Bollen et al., (2010)	DJIA	Twitter feeds	Investigates whether public sentiment in daily twitter posts can be used for stock price prediction
Cheng et al., (2010)	Taiwan Stock Exchange	TSMC stock data	Proposes a hybrid model based on Rough set theory and genetic algorithm forstock price prediction
Dai et al., (2012)	Japanese Stock Market, China Stock Market	Nikkei 225 stock data (80%)	Proposes a hybrid model of NLICA and Neural Network
Wei et al., (2011)	Taiwan Stock Exchange		Proposes an ANFIS model for stock market prediction
Vaisla& Bhatt, (2010)	Indian stock market	NIFTY data	Employed ANN for stock market prediction and compared the result with that of statistical forecasting
Liu et al., (2012)	TAIEX, NASDAQ		Type 2 neuro-fuzzy modelling was applied to stock price prediction
Merh et al., (2010)	Indian stock market		1Developed two hybrid models ANN-ARIMA and ARIMA-ANN and comparison made between the

			two
Zarandi et al., (2012)		IBM, Dell Corporation, British Airways, Ryanair stock data	Proposes a hybrid AI model based on the coordination of intelligent agents for next-day stock price prediction
Kazem et al., (2013)	NASDAQ	80%	Proposes a prediction model based on chaotic mapping, firefly algorithmand SVR for stock market prediction
Asadi et al., (2012)	TSE, TEPIX, DJIA, NASDAQ		Proposes a stock prediction model that uses GA and LMBP to predict stock market indices
Wang et al., (2012)	SZIL, DJIA		Proposes hybrid model of ESM-ARIMA and BPNN for stock market prediction
Ballini et al., (2010)	Brazilian Stock Market	Ibovespa stock data	Proposes a class of neuro-fuzzy network and a constructive learning method for stock market prediction
Wei (2013)	TAIEX	TAIEX dataset	Proposed hybrid of adaptive expectation genetic algorithm and ANFIS for stock price prediction
Majhi et al., (2013)	S&P 500, DJIA Index	S&P 500, DJIA dataset	developed a hybrid prediction model that uses RBF NN and non-dominated sorting multi-objective GA-2
Enke et al., (2011)	S&P 500		Proposes a hybrid 3-stage stock market prediction system
Cai et al., (2013)	Taiwan Stock Exchange	TAIEX dataset	Proposes hybrid of Fuzzy time series Genetic Algorithm for stock price prediction
Anbalagan & Maheswar (2015)	Bombay Stock Exchange	TCS, RIL dataset (80%)	Proposes a Fuzzy Metagraph based model for stock market prediction
Babu& Reddy (2015)	Indian stock market	SBI, Tata Steel dataset	Proposes a hybrid ARIMA-GARCH prediction model
Hadavandi et al., (2010)	IT Sector, Airline Sector	IBM, Dell Corporation, British Airways, Ryanair stock data	Proposes a hybrid model based on genetic fuzzy systemsand ANN for stock price prediction
Hafezi et al., (2015)	German stock market	DAX price dataset	Proposed a hybrid bat-neural network multi-agent system for stock price prediction
Ticknor (2013)		Microsoft Corp, Goldman Sachs Group Incstock	Proposes a Bayesian regularized ANN for financial market behavior prediction

		dataset	
Chang & Fan(2011)	TAIEX	TAIEX stock dataset	Proposes a hybrid ANFIS stock prediction model based on AR and volatility
Hsu et al.,(2009)	TAIEX	TAIEX-FISI dataset	Proposes a hybrid model of SOM and Genetic programming for stock price prediction
Yeh et al., (2010)	TAIEX	TAIEX stock dataset	Proposed a stock prediction model based on SVR with multiple-kernel learning algorithm
Boyacioglu & Avci (2010)	Instanbul Stock Exchange	DJI, DAX, BOVESPA indices, Macroeconomic Indicators, ISE dataset	Proposes the use of ANFIS for stock price prediction
Zahedi et al., (2015)	Tehran Stock Exchange	Tehran Stock Exchange dataset	Applies ANN and Principal Component method using 20 accounting variables for stock price prediction
Tsai et al., (2010)	Taiwan Stock Exchange	Taiwan Economic Journal dataset	Compares the selection methods PCA, GA, and CART then combines them based on union, intersection, and multi-interaction approaches to analyse prediction accuracy and errors.
Atsalakis et al., (2011)	Greece stock market	National Bank of Greece stock dataset	Proposes a stock prediction system that is based on a neuro-fuzzy architecture which uses Elliot Wave Theory
Ballings et al., (2015)		Amadeus Database dataset	Benchmark study of ensembles and single classifier models
Feng & Chou (2011)	Taiwan Stock Exchange	TAIEX stock dataset	Developed an ANN prediction system with the combinations of SRA, Dynamic learning, and Recursive based PSO Learning algorithms
Liao et al., (2010)	Chinese stock market, HIS, DJI, IXIC, SP 500	Chinese stock market dataset	Proposed an improved NN model by introducing a stochastic time effective function
Mostafa (2010)	Kuwait stock Exchange (KSE)	KSE dataset	Forecasts KSE movements using 2 NN architectures: MLPNN and Generalized regression NNs
Shen et al., (2010)	Shanghai Stock Exchange	SSE dataset	Proposes RBF-NN optimizedby Artificial fish swarm Algorithm for stock price prediction
Wang et al.,	Shanghai	Shanghai	Proposed a hybrid stock prediction

(2012)	Stock Exchange	Composite Index closing prices	model based on Wavelet De-noising-based Back propagation NN
Chen et al., (2010)	Taiwan Stock Exchange	TAIEX dataset	Proposes a hybrid model which improves NGBM by Nash equilibrum concept
Anish & Majhi (2015)	DJIA, S&P500	DJIA, S&P 500 Dataset	Proposes a hybrid model of a feedback type of functional link ANN for stock prediction
Lu (2010)	Taiwan Stock Exchange	TAIEX closing cash index, Nikkei 225 opening cash index	Proposes an integrated ICA-based denoising scheme with NN for stock price prediction
Luo & Chen (2012)	Shanghai Stock Exchange	SSE dataset	Proposes a stock prediction model that integrates PLR and WSVM for stock price prediction
Tsai et al., (2010)	Taiwan Stock Exchange	Taiwan Economic Journal dataset	Examines the applicability of classifier ensembles by constructing the homogenous and heterogeneous classifier ensembles for stockprice prediction
Desai et al., (2013)	Indian stock market	S&P CNX Nifty 50 dataset	Proposes the use of ANN for predicting S&P CNS Nifty 50 Index
Yixin & Zhang (2010)	Chinese stock market	Chinese stock market dataset	Uses BP NN for stock market prediction
Wang et al., (2011)	Shanghai Stock Exchange	Shanghai Composite Index dataset	Proposes an ANN stock prediction model based on HLP
Rounaghi et al., (2015)	Tehran Stock Exchange	Tehran Stock Exchange dataset	Uses multivariate adaptive regression splines (MARS) model and semi-parametic splines technique for stock price prediction
Park & Shin (2013)		KOSPI listed companies' stock prices	Proposes a stock prediction model that uses graph based SSL for stock prediction
Ni et al., (2011)	Shanghai Stock Exchange	SSECI dataset	Used of fractal feature selection based on fractal dimension and ant colony algorithm and SVM for stock price prediction
Cocianu& Grigoryan(2015)	Bucharest stock exchange	SNP stock dataset	Proposes a feed-forward NN architecture with gradient descent with adaptive learning rate variant of BP Algorithm for stock price prediction
ZheGao & Yang(2014)	Shanghai and Shenzhen	Shanghai-Shenzhen 300	Proposes a hybrid SVR with hierarchical clustering for stock

	Stock Exchanges	index dataset	price prediction
Abraham AuYeng(2011)	NASDAQ	Nasdaq-100 index, S&P CNX Nifty index dataset	Investigates the representationof stock markets using ensembles by employing an ensemble of ANN-LSM, SVM, Neuro-fuzzy model and Difference boosting NN
Olatunji et al., (2013)	Saudi stock market	Saudi stock market dataset	Proposes the use of ANN model for the prediction of Saudi stock market
Suwandi& Santica(2014)	Indonesian stock exchange	Jakarta composite index dataset, gold fixing price, WTI crude oil price	Developed a least square SVM model to predict daily close price of Jakarta composite index
Nguyen & Le(2014)		IBM, AppleInc, S&P 500, DJI stock dataset	Proposes a stock price prediction model based on the combination of SOM and fuzzy SVM
Adebiyi et al., (2014)	New York Stock Exchange	Dell Inc stock data	Compares the performance of ARIMA and ANN for stock price prediction
Hegazy et al., (2014)	Bombay Stock Exchange	BSE Sensex index dataset	Optimizes FIS parameters by an adaptive network. The optimized model is optimized using Quantum GA for forecasting accuracy refinement
Adebiyi et al., (2012)	Nigerian Stock Exchange	NSE Companies' stock price dataset	Uses a fuzzy-neural network fed with hybrid market indicators for stock price prediction
Chet et al., (2014)	Colombo Stock Exchange	CSE Dataset (80%)	Employed the use of BP ANN for stock price prediction
Neenwi et al., (2013)	Nigerian Stock Exchange	Access bank, First bank, UBA stock dataset	Uses ANN for stock price prediction
Isenah& Olubusoye(2014)	Nigerian Stock Exchange	NSE dataset	Develops two ANN based stock prediction models and compared their performances with an ARIMA model
Magaji& Adeboye (2014)	Nigerian Stock Exchange	Cowry, CashCraft and BGL dataset	Implemented the logistic function on BP algorithm for ANN for stock price prediction
Akintola et al., (2011)	Nigerian Stock Exchange	Intercontinental Bank stock prices	Proposes a neural network based model for stock price prediction
Bola et al., (2013)	Nigerian Stock Exchange	Technical Indicators	Carries out a study of ANN and Bayesian network for stock price

			prediction
Subhabrata et al., (2014)	National Stock Exchange (India)	102 stocks dataset	Proposes a SOM based hybrid clustering technique with SVR for stock price and volatility predictions and for portfolio selection.
Dash & Dash (2016)	Bombay Stock Exchange, US Stock Market	BSE SENSEX stock index, S&P 500 stock index	Proposes a self-evolving recurrent neuro-fuzzy inference system with Modified Differential Harmony Search (MDHS) for stock price prediction.
Lahmiri (2014)	US stock market	S&P 500, Hewlett-Packard, IBM, Microsoft, and Oracle datasets	Proposes the use of low and high frequency components with BP ANN for stock price prediction.
Babu & Reddy (2014)	National Stock Exchange (India)	Simulated dataset, Sunspot data, Electricity price data, L&T company stock	Proposed a hybrid ARIMA-ANN stock prediction model that employs the use of a moving-average filter for one-step ahead and multi-step ahead predictions.
Chang & Liu (2008)	Taiwan Stock Exchange	Taiwan Electronic shares	Developed a TSK type fuzzy rule based system for stock price prediction
Guresen et al., (2011)	NASDAQ Stock Exchange	NASDAQ index dataset	Evaluates the effectiveness of various neural network models in predicting stock market index

Table 2: Summary of Prediction Methodology Employed in each Article

Article	Prediction Model	Input Variables	Training Method	Layers (Neurons)	Data Preprocessing
Chakravarty et al., (2012)	FLIT2NS	Daily closing prices, minimum and maximum price of dataset	BP Algorithm, PSO Algorithm	5	
Fenghua et al., (2014)	Hybrid SSA-SVM	Predictive value closing price	SVM		Yes (SSA)
Kara et al., (2011)	ANN and SVM	Daily closing prices, minimum and maximum price of dataset	BP Algorithm	3(10,-,1)	Yes
Hsieh et al., (2010)	ABC-RNN	10 Technical Indicators, open, close, highest, lowest price	ABC Algorithm		Yes (Wavelet transform)

Sureshkumar et al (2012)		previous close price, open price, high price, close price			
Bollen et al., (2010)	Self-organizing Fuzzy Neural Network	Past 3 days DJIA values and mood values of past 3 days	SOFNN	5	Yes
Cheng et al.,., (2010)	RST-GA	Technical Indicators	RS algorithm, GA algorithm		Yes (CPDA,MEPA)
Dai et al.,., (2012)	NLICA-ANN			3 (4-9-1)	Yes (NLICA)
Wei et al.,., (2011)	ANFIS	Opening price, highest price, lowest price, closing price, trading volume	Least squares method and BP gradient descent method	5	Yes (Correlation matrix, subtractive clustering)
Vaisla & Bhatt (2010)	ANN	Closing price, exchange rate, FII purchase, FII sales			
Liu et al., (2011)	T2NFS	closing stock prices	PSO, Least square estimation	4	Yes (Self constructing clustering method)
Merh et al.,., (2010)	ANN-ARIMA	Daily opening price, high,low and closing prices	BP Algorithm	3	Yes
Zarandi et al.,., (2012)	Fuzzy Multiagent System	index opening, closing price, daily highest and lowest values	Genetic Fuzzy System	4	Yes (Stepwise regression analysis and SOM neural network clustering)
Kazem et al., (2013)	SVR-CFA	Daily closing prices	SVR		Yes
Asadi et al., (2012)	PELMNN	7 Technical Indices	GA and LM	4 (2-4-4-1)	Yes
Wang et al., (2011)	PHM	Opening and Closing index	GA	3 (12-9-12)	
Ballini et al., (2010)	NFN		On-line Learning	5 ,2,1	Yes (First differencing, Logarithmic Transformation)
Wei (2013)	ANFIS-	7 Technical	Least		Yes

	AEGA	Indicators	squares method and BP gradient descent method		
Majhi et al., (2013)		10 Technical Indicators			Yes
Enke et al., (2011)	Fuzzy Type 2 ANN	CDR3 rate, PPI, M1 level index price level, IP reading	Differential Evolution Algorithm	5	Yes
Cai et al., (2013)	FTSGA	Closing index prices	GA		Yes
Anbalagan et al., (2015)		Technical Indicators	FM Learning Algorithm	4	Yes
Babu&Reddy (2015)	ARIMA-GARCH	closing stock prices			Yes
Hadavandi et al., (2010)	CGFS	Open,close,high,low prices	SOM		Yes (Stepwise regression analysis)
Hafezi et al., (2015)	Hybrid BNNMAS	Daily stock data, news	Bat Algorithm	3 (-, 6, 1)	Yes
Ticknor (2013)	Bayesian ANN	Daily stock prices,6 Financial Indicators	Minimization of the mean squared error	3 (9, 5, 1)	-
Chang et al., (2011)	ANFIS based on AR and Volatility	Different-order AR model, different-order momentum	BP Algorithm, Least square method		Yes
Hsu et al., (2011)	SOM-GP	Technical Indicators, daily closing prices			
Yeh et al., (2010)	MKSVR	Daily closing prices, Technical Indicators	SMO, Gradient Projection method		
Boyacioglu & Avci (2010)	ANFIS	6 macroeconomic variables, 3 indices	FIS	5	-
Zahedi et al., (2015)	ANN-PCA	20 accounting variables	LVM	3 (-,10,-)	Yes
Tsai et al., (2010)	ANN	Fundamental Indices,	BP Algorithm	3	Yes (PCA,GA,CART

		macroeconomic indices			)
Atsalakis et al., (2011)	WASP	EWO, Oscillator lags, moving averages of 5 and 35 days	Least squares method and BP method		
Ballings et al., (2015)		Technical Indicators			
Feng & Chou (2011)	ANN	2 Technical Indexes, 5 MA, 6 RSI	PSO-RLS Learning Algorithm s		Yes
Liao et al., (2010)	The stochastic time effective neural model	Daily opening price, high,low, closing prices, and trade volume	BP Algorithm	3 (5-20-1)	Yes
Mostafa (2010)	ANN	Daily closing prices	Quasi-Newton training algorithm, EBP Algorithm, Conjugate gradient descent Algorithm	3 MLP, 4(GRNN)	
Shen et al., (2010)	RBFNN-AFSA	4 Technical Indicators	AFSA	3	Yes
Wang et al., (2011)	WDBPN N	closing prices	BP Algorithm	3 (3-10-3)	Yes (Wavelet transform)
Chen et al., (2010)	NNGBM	daily stock prices	Least square method		Yes
Anish & Majhi (2015)	FA-FFLANN -RLS	3 Technical Indicators	Recursive Least square training, LMB Algorithm	3	Yes (FA)
Lu (2010)	ICA-BPN	Technical Indicators, Futures prices	BP Algorithm	3 (6-13-1)	Yes (ICA)
Luo & Chen (2012)	PLR-WSVM	11 Technical Indicators	WSVM		Yes (PLR)
Desai et al., (2013)	ANN	Closing prices	BP Algorithm	3 (-,10,-)	Yes (Logarithmic First

					Differencing)
Yixin & Zhang (2010)	ANN	Technical Indicators	BP Algorithm	3 (21-3-1)	Yes
Wang et al., (2011)	ANN	daily closing price	BP Algorithm	4 (-,1,1,1)	Yes (HLP)
Rounaghi et al., (2015)	MARS	30 Accounting variables,10 Economic variables			Yes
Park & Shin (2013)	SSL	7 Technical Indicators, 16 Financial Economical indexes	Graph-based SSL		Yes
Ni et al., (2011)	SVM	Technical Indicators	SVM		Yes
Cocianu et al., (2015)	ANN	opening, closing, highest, lowest price, 7 Technical and Fundamental Indicators	BP Algorithm (Adaptive learning rate variant)	2	-
ZheGao & Yang (2014)	HC-SVR	22 Technical Indicators, 4 CSI300 Index futures	SVM (Grid search parameter algorithm)		Yes
Abraham et al., (2011)		opening,closing, highest, lowest price			Yes
Olatunji et al., (2013)	ANN	closing price	BP Algorithm	3	-
Suwandi et al., (2014)	LSSVM	Open, closing, high and low price, Gold fixing price	Grid search technique		Yes
Nguyen et al., (2014)	SOM-F-SVM	EMA 100, RDP-5, RDP-10, RDP-15, RDP-20,RDP+5	Fuzzy Inference System		Yes
Adebiyi et al., (2014)	ANN, ARIMA	open, low, high, close prices and volume traded	BP Algorithm		Yes
Adebiyi et al., (2012)	ANN	10 Technical variables, 8 fundamental analysis variables	BP Algorithm	3 (18-24-1)	-
Sakarya et al., (2015)	ANN	gold price, oil price, interest rate, CPI, exchange rate,	BP Algorithm	4 (7-9-7-2)	Yes

		money supply, BIST volume			
Hegazy et al., (2014)	NFIS-QGA	daily open, close, highest, lowest prices	DCQGA		Yes
Adebiyi et al., (2012)	Neuro-fuzzy model	Technical, fundamental indicators, 5 expert opinions variables	BP Algorithm	3 (21-26-1)	Yes
Chet et al., (2014)	ANN	Daily ASPI, ASTR, PER, PBV data	BP Algorithm	3 (4-8-1)	Yes
Neenwi et al., (2013)	ANN	4-day price movements	BP Algorithm	3	Yes
Isenah et al., (2014)	ANN	Technical Indicators		3	Yes
Magaji (2014)	ANN	Previous day index value, previous day's NGN/USD exchange rate	BP Algorithm	3 (4-2-1)	Yes
Akinola et al., (2011)	ANN	Daily closing price	BP Algorithm	4 (4-4-4-1)	Yes
Guresen et al., (2011)	ANN	Previous 4 days index values	BP Algorithm	-	Yes
Chang & Liu (2008)	TSK-type Neuro-fuzzy network	8 Technical Indices	Simulated Annealing	-	Yes
Babu& Reddy (2014)	ARIMA-ANN	Closing prices	BP Algorithm	-	Yes
Lahmiri (2014)	ANN	Wavelet low and high frequency components	BP Algorithm	3 (2-4-1)	Yes
Dash & Dash (2016)	SERNFIS	Open, high, low and closing stock prices, Technical Indicators	MDHS	7	Yes
Subhabrata et al., (2014)	SOM-K-means-SVR	Closing prices, intra-day volatility	Grid and Pattern Search Algorithms	-	Yes

Table 3: Summary of Comparative Studies

Article	Modeling Benchmark	Performance Measure	Result
Chakravarty et al., (2012)	FLIT2FNS, LLWNN, FLANN, Type 1 FLS	MAPE, RMSE	FLIT2FNS model was superior in terms of prediction accuracy and error convergence speed over other models
Fenghua et al., (2014)	SVM, EEMD-SVM	MSE, MAPE	SSA-SVM model resulted in better prediction accuracy than other models
Kara et al., (2011)	ANN, SVM	RMS	The average prediction performance of ANN model was significantly better than that of the SVM model
Hsieh et al., (2010)	BP-ANN, Fuzzy Time Series, ANFIS	RSME, MAE, MAPE	It's performance was superior to other models
Cheng et al., (2010)	RST,GA, Buy-and-Hold approach	Accuracy, Stock return	The hybrid model outperformed other models
Dai et al., (2012)	BPN, ICA-BPN,PCA-BPN	RMSE, MAD, MAPE	NLICA-ANN model provided better forecasting results evidenced by lower prediction error and higher prediction accuracy
Wei et al., (2011)	Fuzzy time series models	RMSE	Proposed system performs better, has the smallest average and variation of RMSE
Vaisla& Bhatt, 2010	Multiple regression technique	MAE, MSE, RMSE	ANN performs better than statistical forecasting
Liu et al., (2011)	Conventional Regression, ANN, Fuzzy Time Series, SVR	RMSE, MAE, MAPE	T2NFS performs best and has the least RMSE and average RMSE
Merh et al., (2010)	ARIMA-ANN	AAE, RMSE,MAPE, MPSE	Prediction of hybrid ANN-ARIMA model were better than hybrid ARIMA-ANN
Zarandi et al., (2012)	HMM, HMM-ANNGA, HMM-FL, ARIMA, ANN	MAPE	By MAPE evaluation, FMAS outperformed other models
Kazem et al., (2013)	SVR-GA, SVR-CGA, SVR-FA,	MSE, MAPE	SVR-CFA outperformed other models having the

	ANN, ANFIS		least average errors for MSE and MAPE.
Asadi et al., (2012)	BPNN, PENN, PEBPNN, ARIMA	MAPE, POCID, U of Theil, ARV	PELMNN outperformed other methods and improved prediction accuracy
Wang et al., (2011)	ESM, ARIMA, BPNN, RWN, EWH	MAE, RMSE, MAPE, ME, DA	Proposed model provided better forecasting results than other models in terms of prediction errors and accuracy
Ballini et al., (2010)	ANN, ARIMA	RMSE, MAPE, Associated residuals pattern, POCID	The neuro-fuzzy network provided more accurate forecasting
Wei (2013)	Fuzzy time series models	RMSE	The proposed model provided superior prediction accuracy
Majhi et al., (2013)	RBF based forecasting model	MAPE, DA, Theils U, ARV	Proposed model provided superior performance in all cases than the RBF forecasting model
Enke et al., (2011)	Fuzzy type 1 approach	RMSE	The proposed model produced better prediction accuracy
Cai et al., (2013)	Fuzzy time series models	RMSE	The proposed model bears the smallest RMSE, and has the best directional accuracy of forecast results
Anbalagan et al., (2015)	RW model, ANN, SVM	Hit Ratio (%), RMSE,MMRE	Outperformed other models
Babu& Reddy (2015)	ARIMA, GARCH, Wavelet-ARIMA, ANN	MAPE, MaxAPE, MAE, RMSE	It rendered better prediction accuracy
Hadavandi et al., (2010)	HMM, HMM-ANN-GA, HMM-FL, ARIMA, ANN	MAPE	Proposed model outperformed other models
Hafezi et al., (2015)	GA-ANN,GRNN, ERBN	MAPE	Proposed model outperformed other models in terms of prediction accuracy
Ticknor (2013)	Fusion model with weighted average, ARIMA	MAPE	Proposed model performs as well as the more advanced models
Chang et al., (2011)	Conventional Fuzzy time series model,	RMSE	The proposed model outperformed other

	Weighted Fuzzy Time series model		models
Yeh et al., (2010)	SK-SVR, ARIMA, TSK-FNN	RMSE	Proposed model outperformed other models
Atsalakis et al., (2011)	A buy and Hold Strategy	Hit-rate	The proposed system outperformed the Buy and Hold strategy
Ballings et al., (2015)	SVM,AB,RF,KF,LR, NN,KN	Area Under Curve (AUC)	Random forest proved to be the top predictor amongst others followed by SVM, KF, AB, NN, KN & LR
Feng & Chou (2011)	Standard PSO, Recursive-based PSO	RMSE, MAD, MAPE, CP, CD	Proposed system produced the most efficientprediction process
Shen et al., (2010)	RBF-GA, RBF-PSO, ARIMA, SVM, BP	Average Error	The proposed model proved to be useful for parallel computation
Wang et al., (2011)	BP Neural Network	MAE, RMSE, MAPE	Proposed model outperforms conventional BP model
Chen et al., (2010)	GM, NGBM	RPE, ARPE	The proposed model gives more precise results
Anish & Majhi (2015)	PCA-FFLANN-LMS, PCA-FFLANN-RLS, DWT-FFLANN-LMS, DWT-FFLANN-RLS, FA-FFLANN-LMS	MAPE, DA,U of Theil, ARV	The proposed model drastically reduced computation and produced better prediction results
Lu (2010)	RWMmodel, BPN model, Wavelet-BPN	RMSE,MAPE,DA	The proposed model produced the smallest value of RMSE and MAPE and provides better forecasting results
Luo & Chen (2012)	PLR-BPN, BHS	ACC	The proposed model achieved the best prediction accuracy
Tsai et al., (2010)	Ensemble of NNs, decision trees, Logistic regression	Average prediction accuracy, Type 1 and Type 2 errors, Return on Investment	The heterogeneous ensembles performed better than the homogenousones
Desai et al., (2013)	BHS	Accuracy	The proposed model produced high prediction accuracy

Park & Shin (2013)	ANN, SVM	AUC, ROI	The proposed model outperformed other models
Ni et al., (2011)	Information Gain, Symmetrical Uncertainty, Relief F, Correlation-based feature selection, OneR feature selection methods		The proposed feature selection method gives higher prediction accuracy thanthe others
Cocianu et al., (2015)	ARIMA models	MSE	The proposed model produced better results
ZheGao& Yang (2014)	PCA-SVR, GA-SVR	RMSE, NMSE, MAE, DS	The proposed model outperformed other models
Abraham et al., (2011)	SVM, NF, ANN,DBNN, E-1, E-2	RMSE,CC, MAP, MAPE	The ensemble approach based on direct error measure outperformed others
Suwandi et al., (2014)	SVM,ARIMA	RMSE, MAE, MAPE	The proposed model produced better prediction accuracy
Nguyen et al., (2014)	SOM-SVM, RBN, ANFIS	NMSE, MAE, DS	Proposed model produced more accurate results
Adebiyi et al., (2014)	ARIMA, ANN	MSE	Performance of ANN was better in terms of forecasting accuracy
Adebiyi et al., (2012)	ANN with only technical Analysis variables	Hit rate	The hybridized approach produced better prediction accuracy
Hegazy et al., (2014)	ANFIS	MSE	Proposed model produced higher prediction accuracy
Adebiyi et al., (2011)	ANN with only technical Analysis variables, FL-ANN wit single analysis variables, FL-ANN with hybrid market indicators	Hit Rate	The proposed model produced better results
Isenah et al., (2014)	ARIMA	RMSE, MAE,NMSE	ANN based models outperformed the ARIMA model
Bola et al., (2013)	ANN, Bayesian network		Bayesian network outperformed the ANN in terms of prediction power
Dash & Dash	RCEFLANN,	RMSE, MAPE,	The proposed model

(2016)	CEFLANN, ANFIS, RSEFNN	MAE	produced superior prediction performance
Lahmiri (2014)	ARIMA, RW, ANN	MAE, RMSE, MAD	The proposed model outperformed other models in terms of prediction accuracy
Babu& Reddy (2014)	ARIMA, ANN, other variants of ARIMA-ANN	MAE, MSE	The proposed model outperformed other models in terms of prediction accuracy for both one-step and multi-step predictions.
Chang & Liu (2008)	ANN, Multiple Regression Analysis	MAPE	The proposed model outperformed the other models
Guresen et al., (2011)	MLP-ANN, DA-ANN, GARCH-ANN, EGARCH-ANN		MSE, MAD

4. Discussion

Soft computing techniques had been widely used for stock price prediction as reported in the extant literature. This is because of its ability to provide better prediction accuracy above other predictive approaches. ANN continue to be the most popular in the stock price prediction efforts with several types of artificial intelligence algorithms proposed, some with feature selection and parameter setting techniques in a bid to improve its prediction accuracy. Furthermore, several studies have focused on the development of hybrid models for stock price prediction with the view of leveraging the advantages of each constituent technique for better prediction performance. Also, there were considerable efforts to make use of hybrid input variables particularly the use of both technical and fundamental analysis variables resulting in good prediction performance of prediction models. From the different articles reviewed the place of input parameters to the models developed was very significant to the outcome of the models.

The findings from table 1 indicate the various stock market exchange from which experimental data for prediction were obtained for each article reviewed. It also shows the predictive models proposed and developed by each researcher. In table 2, most of the predictive models used by each author require data preprocessing. The prevalent training algorithm used in all the reviewed articles was Backpropagation algorithm. The findings from table 3 presents the outcome of proposed model in each article reviewed in comparison with modelling benchmark techniques in extant literatures for comparative analysis. The performance measure frequently used are RMSE and MAPE respectively.

The findings of this literature survey clearly show that integrating of two or more soft computing techniques with improved selection of input parameters would continue to be a way in which researchers can continue to explore in order to improve predictive models of the stock price prediction.

Conclusion

This study has surveyed published papers that focused on the application of soft computing techniques for stock market predictions. The survey has been presented in three summary tables. Table 1 presents the stock market surveyed, experimental data used, and summary of the objective of each reviewed article. Table 2 describes the prediction methodology employed for each article. Table 3 presents articles that carried out comparative studies of various prediction models in terms of the prediction models that were compared, the performance measure(s) employed for comparison and the result of the comparison study. This study would be useful and guide future researchers appropriately the application of soft computing model to stock price prediction.

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