International Journal of Engineering & Technology, 7 (3) (2018) 1836-1845

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i3.14716
Research paper

Soft computing and bioinspired computing techniques for stock market prediction-a comprehensive survey

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Abstract

Stock Market Prediction (SMP) is one of the most important and hottest topics in business and finance. The main goal of SMP is to develop an efficient technique to predict stock values and achieves accurate results with minimum number of input data. This research paper reviews currently available SMP techniques based on soft computing and bio inspired computing algorithms. Many issues in-volved in the SMP are identified and different techniques are studied along with their merits and demerits to find the most suitable one. This paper also analyses the performance of various techniques with respect to some metrics including MSE, RMSE, MAD, MAPE, AAE and Hit ratio. The reviewed papers are classified in terms of number of input variables, prediction method and evaluation parame-ters used. A tabular representation of all the SMP techniques is presented to facilitate the future comparison. From the reviewed paper, it is noticed that the integration of soft computing with the bio inspired algorithms has the potential to predict the stock market index with high accuracy and achieves best result than soft computing method alone.

Keywords: *Bio Inspired Computing; Discrete Wavelet Transform (DWT); Hybrid; Hit; MAPE; PSO; R2; Stock Market Prediction (SMP); Soft Computing and Technical Indicators*

1. Introduction

The stock market or share market is one of the important and popular investment places where investor can get high profits by investing their resources in shares. Stock market is influenced by many internal and external factors such as political, economic and psychological factors. So, Stock Market prediction (SMP) is regarded as a challenging, hard and very tough task in finance due to time variant, complex, nonlinear, dynamic and uncertainty nature of stock data. Many more algorithms and techniques have been developed and implemented for SMP. But, none of the algorithm or technique has been discovered accurately stock price value, while several attempts have been made.

Soft Computing (SC) is the hybrid of techniques that were designed to find solutions of the complex problems which are too hard to model mathematically.SC consists of neural network, fuzzy logic, probabilistic reasoning, machine learning and evolutionary computing. Due to their approximation, robustness, imprecision, flexibility, cognitive ability, good tolerance and symbolic reasoning, SC techniques have found many applications such as SMP, decision support systems, pattern recognition and process control [1].

Bio inspired computing is an intelligent computing technique and has been developed to surmount the drawback of artificial neural network. Bio inspired computing is a multidisciplinary area based on biology, computer science, cognitive science and robotics. These computing techniques are computational approach and algorithms adapted from the characteristics and life survival techniques of various species from the universe [2], [3], [4].Recently, more and more efforts on integrating SC with natural inspired computing algorithms has become common practice to enhance the prediction accuracy.

The main contribution of this research paper is to provide a review and classify the recently developed techniques like soft computing and bio inspired computing techniques applied on different stock markets to predict the stock market data. In specific, more than 60 papers related to SMP has been reviewed, classified and results are presented in table.

The rest of the paper is organized as follows. Section 2 explains the motivation of this survey. Section 3 presents the techniques used for stock market prediction. Section 4 provides the summary of stock market prediction techniques using soft computing and bio inspired algorithms. Section 5 discusses the major conclusions and findings of the study followed by relevant references.

2. Motivation

Although many researches in the field of SMP, no particular or specific guidelines to predict the stock market accurately have been established. Several techniques within the statistical and technical analysis have used to predict the stock value. However, there is limited research conducted to improve the prediction accu Racy of stock market. MSE, RMSE, AAE, R^2, hit rate and MAPE are some important metrics to be considered for SMP.

The motivation of the survey paper is to explore the existing SC and Bio inspired computing techniques along with their performance measures so that the researchers can select the necessary measures for their work in this area and drawbacks of the existing methods can be overcome.

3. Classification of SMP techniques

Developing an accurate and efficient prediction methodology has always plays an important role in stock market. Future price of stock indexes can be predicted in three major ways: (i) Traditional time series analysis (ii) Intrinsic or Fundamental analysis (iii) Technical or chartist analysis

3.1. Traditional time series analysis

Traditional time series analysis study the past data and endeavors to future estimations of a time series as a linear combination of these past data. Univariate or regression and multivariate or relapse are the two groups of time series analysis [5].

3.2. Fundamental analysis

Fundamental analysis deals with the company performance and profitability to assess its real value by examining various factors such as macroeconomic variable, financial condition, financial news and industrial growth. This analysis helps the investor to gain high profit by making decisions based on past performance of the company, overall economy and its earnings forecast. In fundamental analysis of stock market data some important ratios are defined such as P/B Ratio, P/E Ratio, PEG Ratio, Dividend yield, D/E Ratio and ROE [6-21].

3.3. Technical analysis

Technical analysis uses historic data to identify the stock trends and recurring patterns of stock prices to aid with future predictions. Opening price, closing price, highest price, lowest price and trading volume are generally used data for technical analysis. Furthermore, 56 different parameters, oscillators and indicators have been used by the technical analysis [7], [8], [21]. Table 1 lists the various technical indicators employed for SMP.

[4].Input variables and stock markets

Table 2 list the stock market and number of input variables used by the authors to train and test their proposed model. The papers surveyed in this area focus on predicting the closing price of a single stock or multiple stock market values. However, some authors concentrate on predicting multiple stock values (Ajith et al. [42]; Myungsook et al. [24]; Ritanjali et al. [70]; Tsung-Jung et al.[26];Tarek et al.[36];Savinderjit et al.[35];Guo et al. et al.[65]).

All surveyed paper is classified based on the number of inputs, input data size, pre-processing method, implemented technique, learning method, membership function, and training and test data sets. Surveyed papers in Table 2 are categorized into four major groups. First group uses only closing price of previous day as an input for their developed model. Ping-Feng Pai et al. [15] model the Estman Kodak company, Zhang et al. [54] predict the Shanghai stock market, Swarnava et al. [56] model the S&P 500,Chandra et al.[13] studied the NSE. Second group includes the papers that use closing price, opening price, highest price and lowest price as an input Chen et al. [49] try to forecast Taiwan stock exchange, Zhang et al.[53] model the Shangai stock market in 2002 , Ajith et al. [42] examine the NASDAQ and S&P 500, Lokesh et al. [23] attempt to forecast NSE, Tarek et al. [36] model the NASDAQ, DIJA and S&P 500, NSE is examined by Suresh et al. [25], Ripon [32] attempt to predict the Dhaka stock exchange. Third group focuses on papers that use opening price, closing price, lowest price, highest price, trading volume and average value to forecast the stock market. Singapore stock market examined by Ayob et al. [45], Mahdi et al. [57] model the Tehran stock market, Savinderjit et al.[35] try forecast the NYSE and NASDAQ, Victor et al. [58] model the BSE, Yonghui et al.[64] attempt to forecast the Chinese growth enterprise market index, In 2015,Dhaka stock exchange is studied by Mustain et al.[19], BSE is studied by Kumar et al.[47]. Fourth group includes the papers that use technical indicators for prediction. Number of technical indicators used by the authors various from one to thirty-six. George et al. [41] uses one indicator to model the ASE and NYSE, two indicators are used by Puspanjali et al.[38] to model the NSE , Agrawal et al. [21]studied the NASDAQ using three indicators, some papers uses four indicators including Baek et al.[48] model the Korean stock market, Uduak et al.[75] study Nigerian stock exchange, Acheme et al. [40] try to forecast Nigerian stock market. Three papers uses five technical indicators to model stock market data such as Dong et al.[53] attempt to forecast NASDAQ, Jheng et al.[17] model the Taiwan stock exchange and Rajendran et al.[20] try to forecast S&P 500, Six indicators are used by some authors to forecast the stock values namely Phichhang et al.[10] study the Hong kong stock market, Xiaowei et al.[18] model the S&P 500,Shanghai stock market examined by Liu in 2012 [16] and Osman et al.[14] attempt to forecast the S&P 500. Zhang et al. [53] model the exchange rate, NASDAQ and Dow stock prices are forecasted by Myungsook et al.[24] ,Rohit et al.[22] try to forecast Indian stock market and Essam [34] model the DIJA,NASDAQ and S&P 500 using seven indicators. Dong and Zhou [52]) examine the NASDAQ and Peichang et al. [10]) study the Taiwan stock exchange using eight indicators. Shipra et al. [63] uses nine

Table 1: Technical Indicators

Accumulation/Distribution	Williams' Accumulation/Distribution
Average directional movement	Average True range
Chaykin Oscillator	Average True range Band (Bottom)
Commodity Channel Index(CCI)	Average True range Band (Top)
Commodity Channel Index(CCI) genera	Beta
Directional Movement Index	Beta on Decrease
Directional Movement Rating	Beta on increase
Ease of Movement	Bollinger Band(Bottom)
Herrick Payoff Movement	Bollinger Band(Top)
Minus Directional index	Chaikin's Volatility
Money Flow Index	Keltner channel(Bottom)
Money Flow Index(General)	Keltner channel(Top)
On Balance Volume(OBV)	Mass Index
Plus Directional index	Trading Band(Bottom)
Price and Volume Trend	Trading Band(Top)
Qstick Indicator	True Range
Stochastic oscillator	Aroon Down
Williams' %R	Aroon Up
Velocity	Value oscillator
Market Facilitation Index	Upside/Downside ratio
Negative Volume Index	Acceleration
Positive Volume Index	MACD
Time Series Forecast	Momentum
Vertical Horizontal Filter	Rate-of-Change
Absolute Breath Index	Relative Momentum Index
Absolute Breath Index(Percent)	Relative Strength Index
New Highs/Lows Ratio	TRIX

New Highs-Lows Cumulative	Open-10 TRIN

Table 2: List of Stock Market and Input Variables

Author	Year	Stock market	Input data
Ping-Feng Pai et al.	2005	Eastman Kodak Company	Closing price
Zhang et al.	2007	Shanghai stock market	Closing price
Swarnava et al.	2009	S&P 500	Closing price
Jatinder et al.	2015	BSE	Closing price
Chandra et al.	2016	National stock exchange	Closing price
Chen et al.	2001	Taiwan stock index	Opening price, highest price and closing price
Zhang et al.	2002	Shanghai stock market	Opening price, lowest price, highest price and closing price
Ajith et al.	2003	NASDAQ and S&P CNX NIFTY	Opening price, lowest price, highest price and closing price
Chen et al.	2005a	NASDAQ and S&P CNX NIFTY	Opening price, highest price and closing price
Chen et al.	2005b	NASDAQ and S&P CNX NIFTY	Opening price, highest price and closing price
Lokesh et al.	2011	BSE	Opening price, lowest price, highest price and closing price
Tarek et al.	2011	NASDAQ100, DJIA and S&P500	Opening price, highest price and closing price
Ripon	2016	Dhaka Stock Exchange	Opening price, lowest price, highest price and closing price
Ayob et al.	2001	Singapore stock market	Volume, opening price, lowest price, highest price and closing price
Mahdi et al.	2010	Tehran stock exchange	Lowest price, highest price and average value
Savinderjit et al.	2012	NYSE and NASDAQ	Opening price, lowest price, highest price adjusted closing price and volume
Suresh et al.	2012	NSE	Previous close, open price, lowest price, highest price and closing price
Victor et al.	2013	BSE	Opening price, high, low, closing price and volume
Yonghui et al.	2014	Chinese Growth Enterprise Market Index	Opening price, highest price, lowest price, closing price, and trading volume
Mustain et al.	2015	Dhaka Stock Exchange	Opening price, closing price, high, low price and volume
Kumar et al.	2016	BSE	Opening price, lowest price, highest price and volume
Baba et al.	1992	Japanese Stock	15 Technical indicators
Atiya et al.	1997	NASDAQ,S&P 500	8 Fundamental indicators
Dong et al.	2002	NASDAQ	8 Technical indicators
Baek et al.	2002	Korean stock market	4 Technical indicators
Zhang	2003	Exchange rate	7 technical indicators
Dong et al.	2003	NASDAQ	5 Technical indicators
Arnamo et al.	2004	S&P500	10 technical indicators
Ina khanadelwal et al.	2005	Indian mining data	12 technical indicators
Pei chang et al.	2006	Taiwan stock exchange	8 Technical indicators
Xueshen Sui el al.	2007	Shanghai stock market	12 technical indicators
Myungsook et al.	2007	NASDAQ and Dow stock prices	7 technical indicators
Pei chang et al.	2007	Taiwan stock exchange	5 Technical indicators
Rohit et al.	2008	Indian stock market	7 Technical indicators
Ritanjali et al.	2009	DJIA and S&P500	11 Technical indicators
George et al.	2009	Athens Stock Exchange and the NYSE	1 Technical indicators
Phichhang et al.	2009	Hong Kong stock market	6 Technical indicators
Xiaowei et al.	2009	S&P 500	6 Technical indicators
Agrawal et al.	2010	NASDAQ	3 Technical indicators
Tsung-Jung et al.	2011	Taiwan stock exchange and DIJA	14 Technical indicators
Maha et al	2011	Egyptian stock market	10 Technical indicators
Puspanjali et al.	2012	Indian stock market Indices	2 Technical indicators
Hsuan-Ming et al.	2012	Taiwan stock indexes	18 Technical indicators
Liu Dao	2012	Shanghai stock index	6 Technical indicators
Acheme et al.	2014	Nigerian Stock Exchange	4 Technical indicators
Uduak et al.	2014	Nigerian stock exchange	4 technical indicators
Shipra et al.	2014	Dhaka stock exchange	9 Technical indicators
Guo et al. et al.	2014	Shanghai stock market index & DIJA	29 Technical indicators
Rajendran et al.	2014	S&P500	5 Technical indicators
Osman et al.	2014	S&P500	6 Technical indicators
Guo et al. et al.	2015	Shanghai stock market index	36 technical indicators
Essam	2016	DJIA, NASDAQ-100 and S&P500	7 Technical indicators
Ajith et al.	2001	NASDAQ	7 indexes
Esmaeil	2010	Tehran Stock Exchange Prices Indexes	5 Technical indicators and 13 days PSY and Volume
Amit et al.	2010	National Stock Exchange	Closing price, turnover, global indices, interest rate, inflation, news, currency rate, and crude price
Jheng-Long et al.	2012	7274 news in Chinese word and Taiwan's Stock Market	3 Technical indicators and Pointwise mutual information-SA
Salimi	2012	S&P500	Price index
Rahib et al.	2012	-	Statistical data points
Petr hájek et al.	2013	NASDAQ and NYSE	Fundamental plus news information
Amin et al.	2016	NASDAQ	Last four and nine working days as well as the days of week

Indicators to model the Dhaka stock exchange. Arnamo et al. [43] uses ten indicators to forecast S&P 500, Maha et al. [33] uses ten indicators to study the Egyptian stock market. Ritanjali et al. [70] uses eleven indicators to model DIJA and S&P 500. Ina khanadelwal et al. [69] study the Indian mining data and Shanghai stock market is examined by Xueshen et al. [55] using twelve indicators. Tsung-Jung et al. [26] uses fourteen indicators to model the Taiwan stock and DIJA, Baba et al. [46] study the Japanese stock using fifteen indicators, Taiwan stock is examined by Hsuan et al. [39] using eighteen indicators, Guo et al. et al. [65]) uses twenty-nine indicators to forecast the Shanghai stock and DIJA.

Some papers do not focus on particular indicators or other input variables, but uses price index, SA, news and fundamental variables. An example of index-based prediction study by Ajith et al.

[31] who selected seven indexes from NASDAQ and Salim [77] that uses price index of S&P 500.In 2012, Rahib et al. [74] used statistical data points to model the stock market. Esmaeil [11] examine the Techran stock exchange using five technical indicators, volume and 13 days PSY, Taiwan stock market is studied by Jheng et al. [17] using SA and three technical indicators. Petr hájek et al. [71] uses fundamental variables plus news to model the NASDAQ and DIJA. Amin et al. [28] have utilized last four and nine working days as well as the days of week as an input variable to analyse the NASDAQ stock.

From the surveyed papers, it is observed that selection of input variables plays a vital role in SMP. Each technique used different number of input variable. Pre-processing and selection of indicators as an input may help to eliminate the irrelevant data and enhance the performance of prediction technique. Generally, stock market data has high dimension reducing the effectiveness of training method. Data pre-processing or normalization is used to overcome the above-mentioned issue. Table 3 shows the various pre-processing technique used for SMP. There are many pre-processing techniques are found in the literature including scaling of input data between -1 and 1 or 0 and 1(21 papers) and other techniques employed for data normalization are DWT used by (3 papers), PCA used by Ajith et al. [42] and hybrid of FT and WT used by Peichang et al. [17]. It can be noticed from the reviewed papers that the data pre-processing aids to remove unwanted noisy data and improve the prediction accuracy considerably.

4.1. SMP using soft computing

Summarized form of techniques used to develop prediction model is shown in Table 3. Most of the surveyed paper uses FFNN. Papers that uses FFNN namely Ayob et al. [45]) who employ FFNN with EBP learning algorithm, Zhang et al. [53] uses FFNN with closing price as an input for their model in 2007, Myungsook et al. [24] who uses BPNN with single hidden layer and LM learning algorithm. In 2012, Salim [77] uses MLP with price index as an input to model S&P 500.Amit et al. [27] who utilize BPNN with 45 neurons in single hidden layer and BP learning algorithm, Adebiyi et al. [9] uses BPNN with single hidden layer and sigmoid activation function. The authors have used 18 hybridized indicators as an input for developed model and found the suitable architecture of BPNN is 18/24/1 to predict the stock price accurately. In 2016, Kumar et al. [47] uses BPNN to develop their model for SMP. Some special studies are RNN used by Tsung-jung et al. [26] with ABC learning algorithm in 2011.The authors used wavelet as a pre-processing tool. PNN used by Chen et al. [49] with the architecture of 2/6/2/1.Zhang et al. [54] employed GNN, Baek et al. [48] uses ANN in 2002, Ajith et al. [42] uses FFNN and DBNN to model stock market, Zhquiang et al. [62] uses RBFNN with Purelin activation function and LS learning method. In 2015, Ajithkumar et al. [31] uses recurrent CEFLANN with tangent activation function. Mahdi et al. [57] uses Elman and MLP network with BP learning algorithm. In 2011, Maha et al.[33] utilized MLP and RBF. The network is trained with CGB learning algorithm. Xiaowei et al. [18] uses ESN. The network trained using LS algorithm. Chen et al. [50] developed LLWNN.EDA algorithm is used to train LLWNN. Phichhang et al. [10] presents a comparative study of ten data mining techniques. The techniques are LDA, QDA, K-nearest neighbor classification, Tree based classification, neural network, Bayesian classification with Gaussian process, SVM, LS-SVM, Naïve Bayes based on kernel estimation and Logit model.

About 10% of surveyed paper use neuro-fuzzy, FCM and ANFIS as a prediction tool. Neuro fuzzy networks-based techniques are classified with respect the membership function utilized. Commonly used membership functions are Gaussian, sigmoid and trapezoidal. In 2002, Dong et al. [52] have developed fuzzy systems with trapezoidal membership function. Uduak et al. [75] have presented ANFIS model with four technical indicators and trapezoidal membership function. George et al. [41] have designed ANFIS wit Gaussian two shaped function. Improved version of George et al. [41] is developed by Agrawal et al. in 2010 [21]. This model uses Triangular and trapezoidal function.LS-BP is employed for learning. In 2014, Acheme et al. [40] have presented FIS with Gaussian membership function. Pei chang et al. [76] uses TSK fuzzy with Gaussian function. The performance of TSK fuzzy system is improved using DWT by the same author in 2007.Hsuan et al. [39] developed an ANFIS system to predict the stock trend in 2012.The authors have used hyperactive ellipsoid function. Ajith et al. [42] who uses ANFIS to forecast future price of stock market.

4.2. SMP using bioinspired computing

To reduce the computational complexity of ANN, optimization algorithms or techniques are integrated with ANN. Some commonly use natural inspired algorithms are PSO, FPA, BFO, ABC, DE, BE, MCS and GA. Tarek et al. [36] have developed DRNN which is trained using GA/PSO model with perturbation term. In 2016, Essam [34] have introduced adaptive linear combiner which uses PSOCoM. ABFO and BFO used by Ritanjali et al.[70] in 2009.SVM based prediction model is developed by Choudhry et al. (2008). They have combined GA with SVM to improve the prediction accuracy. Ripon[32] integrates the GA with ANN.GA and SRA is integrated with BPN by Esmaeil [11] in 2010.SRA is used for input variable selection and GA is used for weight optimization

Table 3: Summary of SMP Techniques Studied in the Survey

Author	Year	pre-processing	Duration	Data size	Method	NS/WN	Train	Test	Transfer / Membership function	Learning method
Ajith et al.	2001	PCA	Mar 1999 to Mar 2001	24 M	FFNN and ANFIS	-	80%	20%	-	SCGA
Ayob et al.	2001	Yes	-	1478	FFNN	-	-	-	Sigmoid	EBP
Chen et al.	2001	-	Jan 1982 to Aug 1992	-	PNN	2/6/2/1	Jan 1982 to Aug 1987	Sep 1987 to Aug 1992	-	-
Baek et al.	2002	-	-	28M	ANN	-	-	-	Tansig	LM
Dong et al.	2002	Yes	Jul 1999 to Sep 1999	44150	FUZZY	-	-	-	Trapezoid	-
Zhang et al.	2002	yes	1981 to 1994	-	GNN	-	-	-	-	-
Ajith et al.	2003	-	Jan 1995 to Jan 2002	-	FFNN, DBNN, SVM and ANFIS	4/26/1	50	50	Tanh-sig	LM
Dong et al.	2003	Yes	-	68933	FFNN	5/4/1	-	-	-	-
Zhang	2003	-	1980 to 1993	731	ARIMA-ANN	7/6/1	679	52	-	-
Arnamo et al.	2004	-	-	2000	NXCS	10/8/3/1	1000	1000	-	-
Ping-Feng	2005	-	Oct 2002 to	50	ARIMA-SVM	-	-	-	-	-

et al.			Dec 2002							
Chen et al.	2005a	-	Jan 1995 to Jan 2002	-	fuzzy TS and hierarchical TS fuzzy	-	-	-	-	PSO
Chen et al.	2005b	-	Jan 1995 to Jan 2002	-	LLWNN	3/8/1 and 5/8/1	-	-	-	EDA
Pei chang et al.	2006	-	Jul 2003 to Dec 2005	614	TSK Fuzzy	-	494	120	Gaussian	-
Myungsook	2007	[0.25 0.75]	Mar 2002 to Jan 2005	130	BPNN	7/8/1	110	20	Logsig	LM
Pei chang et al.	2007	WT -FT	-	495	DWT-TSK	Haar	-		Gaussian	-
Xueshen et al.	2007	-	Apr 1997 to Sep 2006	2261	Wavelet -SVM	-	1920	341	Gaussian RBF	-
Zhang et al.	2007	[0.1 0.9]	Jun 1995 to Jun 2003	-	FFNN	-	-	-	Sigmoid	EBP
Rohit et al.	2008	-	Aug 2002 to Jan 2008	1386	GA-SVM	-	832	278	Polynomial kernel	-
George et al.	2009	-	Jan1986 to Mar 2005	4,775	ANFIS	-	-	-	Gaussian-2 shaped	-
Phichhang Ou et al.	2009	-	Jan 2000 to Dec 2006	1732	Ten data mining methods	-	1482	250	-	-
Ritanjali et al.	2009	[-1,1]	Jan 1994 to Oct 2006	3228	Simple linear combiner (ABFO and BFO)	-	2510	718	-	-
Swarnava et al.	2009	-	Jan 2003 to Mar 2009	-	DWT-BPNN	Db5, Coif 4 Sym 7	-	-	Tansig-purelin	LM
Xiaowei et al.	2009	[-1 1]	Dec 2001 to Nov 2005	1100	PCA-ESN	-	1000	100	-	LS
Amit et al.	2010	[0 1]	198 to 2008	3500	BPNN	45/45/1	3300	200	Sigmoid	BP
Esmaeil	2010	[-.0.9 0.9]	Apr 2006 to Jan 2009	863	SRA-GA-BPNN	2/4/4/1	694	169	Sigmoid-tanh	BP
Mahdi et al.	2010	[-1 1]	2000 to 2005	-	MLP and Elman network	-	-	-	-	BP
Agrawal et al.	2010		Apr 2007 to Apr 2008	78	ANFIS		53	25	Triangular/ Trapezoidal	LS-BP
Lokesh et al	2011	-	-	259	GA-time series	-	-	-	-	-
Maha et al.	2011	yes	1998 to 2009	-	MLP, RBF and SVM	-	1999-2004	2005-2009	-	CGB
Tarek et al.	2011	-	Jan 2000 to Feb 2011	-	SDRNN	-	Jan 2000 to Jan 2006	Jan 2006 to Feb 2011	-	GA/PSO
Tsung-Jung et al.	2011	DWT	1997 to 2003	-	RNN	10/4/1	83%	17%	-	ABC
Adebiyi et al.	2012	-	-	-	BPN	18/24/1	-	-	Sigmoid	BP
Hsuan-Ming et al.	2012	-	Jan 2000 to Dec 2004	-	PSO-RLS-ANFIS	-	-		hyper-ellipsoid	
Jheng-Long et al.	2012	-	Jan 2012 to Apr 2012-news	-	SVM	-	-	-	RBF	-
Liu Dao	2012	yes	Oct 1991 to Mar 2011	4736	SVM	-	-	-	Gauss function	-
Puspanjali et al.	2012	[0 1]	Mar 2000 to Mar 2012	3019	FLANN (BP and DE		1200	400	tanh	LM
Rahib et al.	2012	[0 1]	-	1000	FWNN	3/8/1	950	50	-	DE
Salim	2012	DWT	Oct 2003 to Jan 2008	-	MLP	-	80%	20%	Hyperbolic	BFGS-LM
Savinderjit et al.	2012	[-1 1]	Apr2009 to Mar 2011	700	DE-SVM	5/11/1	500	200	RBF	-
Petr hájek et al.	2013	yes	-	685	MLP, GA-RBF, SVR	-	80%	20%	Logistic, Linear polynomial and RBF	Conjugate gradient method
Victor et al.	2013	[0 1]	Jan 2012 to Nov 2013	-	ANN	-	70%	30%	Sigmoid	BP
Acheme et al.	2014	-	Jan 2012 to Jun 2012	236	FIS	-	-	-	Gaussian	-
Guo et al. et al.	2014	-	Jan 2003 to Dec 2005	1180	ICA-CCA-SVR	-	726	242	-	-
Rajendran et al.	2014	-	2002 to 2012	273d	FCM-NN	5/ 50/ 25/ 10/2/ 1	-	-	Sigmoid	RP
Shipra Banik et al.	2014	-	Jan 2004 to Dec 2012	-	ANN_RS	9/12/14/1	-	-	Sigmoid	BP
Uduak et al.	2014	-	3 years	-	ANFIS	-	-	-	Trapezoidal	-

Yonghui et al.	2014	-	May 2013 to Aug 2013	58d	BP-Markov chain	-	41d	17d	-	-
Ajit et al.	2015	[0 1]	Jan 2004 to Dec 2008	1200	Recurrent CEFLANN	-	800	400	Tanh	PSO,HMRPSO and DE
Guo et al. et al.	2015	-	Jan 2000 to Dec 2004	1200	PCA-RBFNN	-	957d	243d	Purelin	LS
Jatinder et al.	2015		Jan 2012 to Dec 2014	-	ARIMA-DWT	-	-	-	-	-
khandel-wal et al.	2015	DWT	Apr 1981to Mar 1998	-	ARIMA-ANN	12/9/1	204	30	-	-
Mustain et al.	2015	yes	Jan 2013 to Apr 2015	600	ANN and ANFIS	5/10/1	500	100	Tan-linear/ four gbell	-
Osman et al.	2015	-	Feb 2000 to 2014	-	FPA-LS-SVM, BA-LS-SVM, MCS-LS-SVM, ABC-LS-SVM, and PSO-LS-SVM	-	70%	30%	-	-
Amin et al.	2016	-	Jan2015 to Jun 2015	99d	-	20/40/20/1	60%	20%	Tan and logistic	LM, OSS and GDA
Chandra et al.	2016	-	Jan 2006 to Mar 2016.	-	BPNN	-	-	-	Log sig	-
Essam	2016	-	Jan 2005 to Dec 2014	2500	Adaptive linear combiner (PSO-CoM)	-	1500	1000	-	-
Jatinder et al.	2016	-	Jan 2009 to Dec 2012	-	DWT- Technical indicators	Db2	-	-	-	-
Kumar et al.	2016	-	Jan 2010 to Jun 2015	1414	DWT-BPNN	Haar	80%	20%	-	LM
Ripon	2016	-	Jan 2014 to Dec 2014	12M	GA-ANN	-	-	-	-	BP

"-":Not mentioned in the paper

Table 4: Comparison of Prediction Techniques

Author	Year	Anns	ANFIS	Bioinspired Computing	Dwt Based Meth-od	Others
Atiya et al.	1997		✓			
Ajith et al.	2001	✓	✓			
Ayob et al.	2001	✓				
Chen et al.	2001	✓				
Baek et al.	2002	✓				
Dong et al.	2002		✓			
Zhang et al.	2002	✓				
Ajith et al.	2003	✓	✓			
Dong et al.	2003	✓				
Zhang	2003					✓
Arnamo et al.	2004	✓				
Chen et al.	2005a		✓			
Chen et al.	2005b				✓	
Ping-Feng et al.	2005					✓
Pei chang et al.	2006		✓			
Myungsook	2007	✓				
Pei chang et al.	2007				✓	
Xueshen et al.	2007				✓	
Zhang et al.	2007	✓				
Rohit et al.	2008			✓		
George et al.	2009		✓			
Phichhang et al.	2009					✓
Ritanjali et al.	2009			✓		✓
Swarnava et al.	2009				✓	
Xiaowei et al.	2009	✓				
Amit et al.	2010	✓				
Esmaeil	2010			✓		
Mahdi et al.	2010	✓				
Agrawal et al.	2010		✓			
Lokesh et al.	2011			✓		
Maha et al.	2011	✓				
Tarek et al.	2011			✓		
Tsung-Jung Hsieh	2011	✓				
Adebiyi et al.	2012	✓				
Hsuan-Ming et al.	2012			✓		
Jheng-Long et al.	2012					✓
Liu Dao	2012					✓
Puspanjali et al.	2012			✓		
Rahib et al.	2012				✓	
Salim	2012	✓				
Savinderjit et al.	2012			✓		
Petr hájek et al.	2013	✓		✓		
Victor et al.	2013	✓				

Acheme et al.	2014		✓			
Rajendran et al.	2014					✓
Shipra Banik et al.	2014	✓				
Uduak et al.	2014		✓			
Yonghui et al.	2014					✓
Guo et al. Guo et al.	2014					✓
Ajit et al.	2015	✓				
khandelwal et al.	2015					✓
Jatinder et al.	2015				✓	
Mustain et al.	2015	✓	✓			
Osman et al.	2015			✓		
Guo et al. et al.	2015	✓				
Chandra et al.	2016	✓				
Essam	2016					✓
Jatinder et al.	2016				✓	
Kumar et al.	2016				✓	
Ripon	2016			✓		

Table 5: Evaluation Parameters and Performance Comparison

Authors	Evaluation parameters	Performance
Chandra et al.	MAPE, MAD,RMSE	Prediction accuracy of ANN increased by increasing the number of input data.
Acheme et al.	Buy, sell or hold	Proposed system identify the opportunities and evaluate recommendation from inputs
Essam	MSE, MAPE	Prediction accuracy is superior than other PSO based model
Ritanjali et al.	MAPE	Computationally more efficient and faster convergence
Rohit et al.	Hit rate	Fused model GA-SVM outperforms than SVM alone model
Yonghui et al.	MSE	It yields good prediction accuracy
Chen et al.	MAP,MAPE,CC,RMSE	Investment strategy based on PNN provides better result than other strategy
Chen et al.	CC,MAP,MAPE	Hybrid system improves the prediction accuracy
Dong et el.	MAR and CAR	It offers superior precision in interpreting and identifying the technical patterns
Zhang et al.	Error	GNN gives better result than BP
Zhang et al.	TAD,AAE	The proposed method prevent the over fitting problem
Ajity et al.	MAP,MAPE,CC,RMSE	DBNN gives lowest MAP than other techniques
Arnamo et al.	HIT, Profit	Improved prediction accuracy
Ping-Feng et al.	MAE,MAPE,MSE,RMSE	Hybrid model reduces the forecasting error
Xueshen et al.	Hit ratio	De-noising the training data can improve the prediction accuracy
Myungsook	MSE	Short MA along with longer MA able to capture stock trend
Tsung-Jung et al.	RMSE,AAE,R^2,MAPE, Theil U	This method outperforms than FFNN
Salim	RMSE, MAE, MAPE, ARV, CoV, MAD	Wavelet transform helps to improve the accuracy
Ripon	MSE,MAE,RMSE,MMRE	Improved performance
khandelwal et al.	MSE,MAPE	This approach gives best result than ANN model
Zhang	MSE,MAD	Fusion strategy gives better result
Jatinder et al.	MAE,RMSE,MAPE	Improved accuracy
Jatinder et al.	RMSE,MAPE	SMA is better than ES
Rahib et al.	RMSE	FWNN with DE outperforms
Peichann et al.	MAPE	It achieves accuracy of 96.7%
George et al.	MSE,RMSE,MAE	This method gives superior performance in terms of accuracy
Swarnava et al.	RMSE	It outperforms than GARCH approach
Phichhang et al.	Hit rate and Error rate	LSSVM performs better than other data mining methods
Xiaowei et al.	Average percentage error	ESN gives better result than BPNN
Esmaeil	MAPE	This approach able to predict the stock prices
Agrawal et al.	Success rate	It achieves higher success rate
Amit et al.	Hit rate	Stock news helps to improve the accuracy
Mahdi et al.	MAD,MSE,MAPE,RMSE	MLP gives best result than Elman and LR
Lokesh et al.	Accuracy	GA-TSA system improves the prediction accuracy significantly
Tarek et al.	MAX,MAPE and RMSE	It provides better result than other methods.
Hsuan-Ming et al.	RMSE,MAPE,MAD,DS,CP,CD	PSO-RLS-ANFIS yields good accuracy
Liu Dao	MAPE,RMS	SVM based method gives better result than chaos theory based method
Jheng-Long et al.	MAE,MAPE,RMSE	Combination of SA with technical indicators improves the prediction accuracy than SA alone
Petr hájek et al.	MSE,R^2	Performance better than linear regression model
Suresh et al.	CC,AAE,MAP, RMS and accuracy	It proves NN offer the ability to predict the stock trend
Savinderjit et al.	MSE	Normalization improves the accuracy
Puspanjali et al.	MAPE and RMSE	It gives higher performance
Victor et al.	MAPE, MAD and RMSE	Prediction accuracy of NN improved by increasing the number of input
Shipra et al.	Confusion matrix	Hybrid model has higher precision than NN and rough set based model
Guo et al. et al.	R^2,MAE,MAPE, MSE and RMSE	Better than other SVR approach
Rajendran et al.	MAPE, MSE, RMSE and MAD	FC-ANN method provides better result than ANN.
Osman et al.	RMSE, MAE, SMAPE, and PMRE	It prevents the local minima and over fitting issues found in ANN and SVM
Guo et al. et al.	PCD, R^2, r1, r2, MAPE, HR, TR, RMSE and SMAPE	2D PCA-RBFNN outperforms than PCA-RBFNN and ICA-RBFNN
Ajit et al.	RMSE ,AMAPE and MAPE	FLANN trained with DE current best gives best result
Mustain et al.	RMSE and R^2	ANFIS has the ability to predict the stock market
Amin et al.	MSE and R^2	ANN with OSS training achieve good accuracy
Kumar et al.	RMSE ,MAE, MAD and CoV	It provides higher prediction accuracy

Husan et al. [39] combined PSO, RLS and ANFIS to develop an efficient technique for forecasting. SVM is integrated with DE by Savinderjit et al. [35].RBF kernel is employed. In 2012, Puspanjali et al. [38] uses FLANN.DE and BP is combined with FLANN to increase the prediction accuracy. Osman et al. [14] have used five bio inspired algorithm to optimize and train SVM. The algorithms are FPA, BA, MCS, ABC and PSO.

4.3. Other fusion techniques

To improve prediction accuracy, remove noisy data and reduce the number of input variables required, some technique are combined with other methods for example DWT-TSK is developed by Peichang et al. [10],Yonghui et al. [64] combined BP-markov model and the model is trained using improved BP algoithm. Arnamo et al.[43] used NXCS with the architecture of 10/8/3/1.ARIMA-SVM model is developed by Ping et al. [15] in 2005.Xueshen et al.[55] have presented wavelet-SVM. Zhang et al.[71] and khandelwal et al. [69] integrated ARIMA with ANN. Structure of the developed models are 7/6/1 and 12/9/1 respectively. DWT-ARIMA is developed by Jatinder et al. [72].Swarnava et al. [56] have presented a combined model DWT-BPNN .LM algorithm is used to train the developed model. In 2014, Guo et al. [65] integrated ICA-CCR-SVR to increase the prediction accuracy. Table 4 presents the prediction model developed by researchers.

4.4. Evaluation parameters and future comparison

Table 5 lists the evaluation parameters used along with their futures to estimate the performance of each developed technique. These parameters are categorized into two type's namely statistical and non-statistical parameters. There are many statistical metrics are available in the literature such as MAPE, RMSE, MAE, MSE, MAX and MSPE. Some statistical indicators also used such as include MAD; R^2 and Std. Hit rate is one of the non-statistical measures used by some authors that measure the percentage of accurate prediction of the technique. In addition to, confusion matrix and error are also employed to measure the performance of the method. Yumiu et al. has used Theil U Inequality coefficient which is differ from others.

4. Conclusion and future enhancement

This paper presented a survey and classification of SMP techniques that uses soft computing and bio inspired computing algorithms to predict the stock values. The papers have focused on the number of input variables, prediction method, stock data and evaluation parameters used. It can be seen that each author has used different terms for the evaluation of their developed technique. From the review, it is found that there is still lot of work to be done in the area of SMP. Some open research issues related to this domain are discussed below. It has been observed that there is no standard technique or algorithm to address all the issues involved in SMP. Techniques included in this survey have used simulation to test and evaluate the performance of their proposed method. These techniques must be tested in real world scenarios. It will give realistic assessment of the techniques. It is also inferred from this survey many techniques compare their results with very basic method like ARIMA and do not compare the proposed with the existing techniques which are already better than the basic method. So, lot of experimentation is needed to analyze the effective ones.

Appendix: Type of Prediction Method

ABC	Artificial Bee Colony
ABFO	Adaptive Bacterial Foraging Optimization
ANFIS	Adaptive Neuro Fuzzy Interference System
BA	Bat algorithm
BFGS	Broyden-Fletcher-Goldfarb-Shanno
BFO	Bacterial Foraging Optimization
CCA	Canonical Correlation Analysis
DBNN	Difference Boosting Neural Network
EBP	Error Back propagation
DWT	Discrete Wavelet Transform
ESN	Echo State Network
FC	Fuzzy Clustering
FIS	Fuzzy Interference System
FLANN	Functional Link Artificial Neural Network
FPA	Flower Pollination Algorithm
FT	Fourier Transform
FWNN	Fuzzy Wavelet Neural Network
GA	Genetic Algorithm
GNN	Granular Neural Networks
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
LLWNN	Local Linear Wavelet Neural Network
LR	Linear Regression
LS SVM	Least Squares Support Vector Machine
MCS	Modified Cuckoo Search
MLP	Multilayer perceptron
NXCS	Hybrid system that integrates extended classifier system with Gene
PCA	Principle Component Analysis
PNN	Probabilistic Neural Network
PSO	Particle Swarm Optimization
PSOCoM	Particle Swarm with Center of Mass
QDA	Quadratic Discriminant Analysis
RBFNN	Radial Basis Function Neural Network
RCEFLANN	Recurrent Computationally Efficient Functional Link Neural Netw
RLS	Recursive Least-Squares
RNN	Recurrent Neural Network
RS	Rough Set
SA	Sentimental Analysis
SDRNN	Sigmoid Diagonal Recurrent Neural Network
SRA	Stepwise Regression Analysis
SVM	Support Vector Machine
SVR	Support Vector Regression
TSK	Takagi–Sugeno–Kang
TSA	Time Series Analysis
WN	Wave Name

Learning method

BP	Back Propagation
CGB	Powel-Beale conjugates gradient back-propagation method
DE	Differential evolution
EDA	Estimation of Distribution Algorithm
LM	Levenberg-Marquardt
LS	Least Squares
SCGA	Scaled Conjugate Gradient Algorithm

Evaluation parameters

ARV	Average Relative Variance
CAR	Cumulative Abnormal Return
CD	Correct down-trend
CoV	Coefficient of Variation
CP	Correct up-trend
HR	Hit Rate
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAR	Mean Abnormal Return
MAX	Maximum Absolute Difference
PCD	Percentage of Correct Direction
r1	Correlation coefficient between actual value and prediction value
r2	Autocorrelation coefficient between actual return and prediction return
RMSE	Root Mean of Squared Errors
ROE	Returns on Equity
SMAPE	Symmetric Mean Absolute Percentage Error
TAD	Trend Accuracy in Direction
Theil U	Theil's inequality coefficient
TR	Total Return

General terms

CPACC	Closing Price Acceleration
HPACC	High Price Acceleration
P/B	Price-to-Book
P/E	Price-to-Earnings
PSY	psychological line
PVT	Price Volume Trend
TAIEX	Taiwan stock indexes

References

[1] Kurhe A.B., Satonkar S.S., Khanale P.B. and Shinde Ashok (2011)," Soft Computing and its Applications", Bioinfo Soft Computing 1(1), pp-05-07.

[2] Antony Arul Raj and Sumathi P, (2016)," A Brief Study on Bio - Organism Behavior Inspired Computing Techniques and It's Applications", International Journal of Innovative Research in Computer and Communication Engineering, 4(10), pp.17436-17444.

[3] Binitha S, Siva Sathya S (2012), "A Survey of Bio inspired Optimization Algorithms", International Journal of Soft Computing and Engineering, 2(2).

[4] Jianjun Ni, Liuying Wu, Xinnan Fan, and Simon X. Yang, (2015), "Bioinspired Intelligent Algorithm and Its Applications for Mobile Robot Control: A Survey", Computational Intelligence and Neuroscience, https://doi.org/10.1155/2016/3810903.

[5] Kopperundevi S (2015)," Prediction of future stock prices exploiting machine learning techniques", Phd thesis.

[6] Mritunjay Sharma (2014),"Survey on stock market prediction and performance analysis", International journal of Advanced research in computer engineering and technology, 3 (1), pp.131-135.

[7] Chaigusin, S. (2011),"An investigation into the use of neural networks for the prediction of the stock exchange of Thailand", Doctor of Information Technology, thesis.

[8] Sriram lakshminarayanan(2005)"An integrated stock market forecasting model using neural networks"MSc thesis.

[9] Adebiyi Ayodele A., Ayo Charles K., Adebiyi Marion O., and Otokiti Sunday O,(2012)" Stock Price Prediction using Neural Network with Hybridized Market Indicators", Journal of Emerging Trends in Computing and Information Sciences, 3(1),1-9.

[10] Phichhang Ou and Hengshan Wang, (2009)," Prediction of Stock Market Index Movement by Ten Data Mining Techniques", Modern Applied Science, 3(12), 28-42. https://doi.org/10.5539/mas.v3n12p28.

[11] Esmaeil Hadavandi, (2010)," Developing an Evolutionary Neural Network Model for Stock Index Forecasting", Conference Paper in Communications in Computer and Information Science, · Source: DBLP, 407-415. https://doi.org/10.1007/978-3-642-14831-6_54.

[12] Wen chen and Yixiang Tian, (2016),"Short-term prediction of Stock index Based on EMD and SVMs",International journal of multimedia and ubiquitous Enineering,11(8),1-12. https://doi.org/10.14257/ijmue.2016.11.8.01.

[13] Chandra Shakher Tyagi,Harpreet Singh,Varun Bhardwaj,Kritika Nagpal, (2016)," Applications of Artificial Neural Network in Forecasting of Stock Market Index", International Journal of Recent Research in Mathematics Computer Science and Information Technology ,3(1),28-38.

[14] Osman Hegazy, Omar S. Soliman and Mustafa Abdul Salam, (2015)," Comparative Study between FPA, BA, MCS, ABC, and PSO Algorithms in Training and Optimizing of LS-SVM for Stock Market Prediction", International Journal of Advanced Computer Research, 5(18), 35-45.

[15] Ping-Feng Pai, Chih-Sheng Lin,(2005)," A hybrid ARIMA and support vector machines model in stock price forecasting", The International Journal of Management, 33,497 – 505. https://doi.org/10.1016/j.omega.2004.07.024.

[16] Liu Dao-wen, (2012)," Modelling for Nonlinear Series Prediction based on the Support Vector Machine Theory", National Conference on Information Technology and Computer Science (CITCS 2012), 922-925.

[17] Jheng-Long Wu , Chen-Chi Su , Liang-Chih Yu and Pei-Chann Chang,(2012)," Stock Price Predication using Combinational Features from Sentimental Analysis of Stock News and Technical Analysis of Trading Information", DOI: 10.7763/IPEDR. 2012. V55. 8, 39-430. https://doi.org/10.7763/ipedr.

[18] Xiaowei Lin, Zehong Yang and Yixu Song, (2009)," Short-term stock price prediction based on echo state networks", Expert Systems with Applications, 36, 7313–7317. https://doi.org/10.1016/j.eswa.2008.09.049.

[19] Mustain Billah, Sajjad Waheed and Abu Hanifa, (2015)," Predicting Closing Stock Price using Artificial Neural Network and Adaptive Neuro Fuzzy Inference System (ANFIS): The Case of the Dhaka Stock Exchange", International Journal of Computer Applications, 129 (11), 1-5. https://doi.org/10.5120/ijca2015906952.

[20] Rajendran Sugumar, Alwar Rengarajan and Chinnappan Jayakumar,(2014)," A technique to stock market prediction using fuzzy clustering and artificial neural networks", Computing and Informatics, 33, 992-1024.

[21] Agrawal, S., Jindal, M., Pillai, G. N.(2010), "Momentum Analysis based Stock Market Prediction using Adaptive Neuro-Fuzzy Inference System (ANFIS)", Proceedings of the International Multi Conference of Engineers and Computer Scientists, Hong Kong, 1,March 17 -19, 2010.

[22] Choudhry, R., Garg, K (2008) "A Hybrid Machine Learning System for Stock Market Forecasting", World Academy of Science, Engineering and Technology, Vol. 15,315-318.

[23] Lokesh; Pandey, Anvita; Srivastava, Saakshi; and Darbari, Manuj (2011) "A Hybrid Machine Learning System for Stock Market Forecasting," Journal of International Technology and Information Management, 20 (1), Article 3. Available at: http://scholarworks.lib.csusb.edu/jitim/vol20/iss1/3.

[24] Myungsook Maha Abdelrasoul,(2007)," Investigation of Some Technical Indexes in Stock Forecasting Using Neural Networks", International Journal of Computer, Electrical, Automation, Control and Information Engineering,1(5),1438-1442.

[25] Sureshkumar. K.K and Elango, N.M (2012)," Performance Analysis of Stock Price Prediction using Artificial Neural Network", Global Journal of Computer Science and Technology, 12(1).

[26] Tsung-Jung Hsieh, Hsiao-Fen Hsiao and Wei-Chang Yeh (2011)," Forecasting stock markets using wavelet transforms and recurrent neural networks: An integrated system based on artificial bee colony algorithm", 11 (2), pp.2510-2525.

[27] Amit Ganatr and Kosta.,Y.P,(2012)," Spiking Back Propagation Multilayer Neural Network Design for Predicting Unpredictable Stock Market Prices with Time Series Analysis", International Journal of Computer Theory and Engineering,2(6),963-971.

[28] Amin Hedayati Moghaddam, Moein Hedayati Moghaddam and Morteza Esfandyari,(2016)," Stock market index prediction using artificial neural network", Journal of Economics, Finance and Administrative Science,21,89–93. https://doi.org/10.1016/j.jefas.2016.07.002.

[29] Yuehui Chen, Ajith Abraham, Ju Yang, and Bo Yang,(2005)," Hybrid Methods for Stock Index Modeling", Springer-Verlag Berlin Heidelberg, 1067–1070,

[30] Md. Rafiul Hassan and Baikunth Nath, (2005)," Stock Market Forecasting Using Hidden Markov Model: A New Approach", Proceedings of the 2005 fifth International Conference on Intelligent Systems Design and Applications (ISDA'05), https://doi.org/10.1109/ISDA.2005.85.

[31] Ajith Abraham , Baikunth Nath and Mahanti,(2001)," Hybrid Intelligent Systems for Stock Market Analysis", , In proceedings of International Conference on Computational Science - ICCS 2001, San Francisco, CA, USA337-345.

[32] Kazi Shah Nawaz Ripon,(2016)," Stock Market Forecast Using Bio-Inspired Computing", 3rd IEEE International Conference on Control, Decision and Information Technologies (CoDIT'16), At Malta.

[33] Maha Abdelrasoul, Gamal Selim and Mohamed Waleed Fakhr,(2011)," Stock Market Trend Prediction Model for the Egyptian Stock Market Using Neural Networks and Fuzzy Logic", Bio-Inspired Computing and Applications - 7th International Conference on Intelligent Computing, ICIC 2011, Zhengzhou,China, August 11-14.

[34] Essam El. Seidy, (2016)," A New Particle Swarm Optimization Based Stock Market Prediction Technique", International Journal of Advanced Computer Science and Applications, 7 (4), 322-327.

[35] Savinderjit Kaur and Veenu Mangat, (2012) "Improved Accuracy of PSO and DE using Normalization: an Application to Stock Price Prediction," International Journal of Advanced Computer Science and Applications,3 (9),197-205 https://doi.org/10.14569/IJACSA.2012.030930.

[36] Tarek Aboueldahab and Mahumod Fakhreldin,(2011) "Prediction of Stock Market Indices using Hybrid Genetic Algorithm / Particle Swarm Optimization with Perturbation Term," In proceeding of the International Conference on Swarm Intelligence, Cergy, France, June 14-15.

[37] Alaa Sheta, Hossam Faris and Mouhammd Alkasassbeh, (2013) "A Genetic Programming Model for S&P 500 Stock Market Prediction," International Journal of Control and Automation, 6 (5), 303-314. https://doi.org/10.14257/ijca.2013.6.6.29.

[38] Puspanjali Mohapatra, Alok Raj and Tapas Kumar Patra,(2012) "Indian Stock Market Prediction Using Differential Evolutionary Neural Network Model," International Journal of Electronics Communication and Computer Technology, 2(4), 159-166.

[39] Hsuan-Ming Feng and Hsiang-Chai Chou, (2012), "Evolutionary Fuzzy Stock Prediction System Design and Its Application to The Taiwan Stock Index," International Journal of Innovative Computing, Information and Control, 8(9), 6173-6190.

[40] Acheme David Ijegwa Vincent Olufunke Rebecca Folorunso Olusegun and Olusola Olasunkanmi Isaac, (2014)," A Predictive Stock Market Technical Analysis Using Fuzzy Logic", Computer and Information Science, 7 (3), 1-17. https://doi.org/10.5539/cis.v7n3p1.

[41] George S. Atsalakis and Kimon P. Valavanis, (2009)," Forecasting stock market short-term trends using a neuro-fuzzy based methodology", Expert Systems with Applications, 36, 10696–10707. https://doi.org/10.1016/j.eswa.2009.02.043.

[42] Ajith, A., Sajith, N., and Sarathchandran, P. P. (2003),"Modelling chaotic behaviour of stock indices using Intelligent Paradigms", Neural, Parallel & Scientific Computations Archive, 11, 143–160.

[43] Armano, G., Marchesi, M., and Murru, A. (2004)," A hybrid genetic-neural architecture for stock indexes forecasting. Information Sciences", 170(1), 3–33. https://doi.org/10.1016/j.ins.2003.03.023.

[44] Atiya, A., Noha Talaat and Samir Shaheen, (1997)," An efficient stock market forecasting model using neural networks",In Proceedings of the IEEE International Conference on Neural Networks.

[45] Ayob, M., Nasrudin, M. F., Omar, K., and Surip, M. (2001),"The effects of returns function on individual stock price (KLSE) prediction model using neural networks", In Proceedings of the International Conference on Artificial Intelligence, IC-AI 2001 (pp. 409–415).

[46] Baba, N., and Kozaki, M. (1992),"An intelligent forecasting system of stock price using neural networks", Proceedings of the IEEE International Joint Conference on Neural Networks, 371–377. https://doi.org/10.1109/IJCNN.1992.287183.

[47] Kumar Chandar S, Sumathi M and Sivanandam SN (2016)," Prediction of Stock Market Price using Hybrid of Wavelet Transform and Artificial Neural Network", Indian Journal of Science and Technology,9(8),PP.1-5.

[48] Baek, J., and Cho, S. (2001),"Time to jump. Long rising pattern detection in KOSPI 200 future using an auto-associative neural network",ICONIP, Shanghai,china,160-165.

[49] Chen, A. S., Leung, M. T., and Daouk, H. (2001)," Application of neural networks to an emerging financial market: Forecasting and trading the Taiwan Stock Index",Computers and Operations Research, 30, 901–923. https://doi.org/10.1016/S0305-0548(02)00037-0.

[50] Chen, Y., Dong, X., and Zhao, Y. (2005)," Stock index modelling using EDA based local linear wavelet neural network. Proceedings of International Conference on Neural Networks and Brain, 1646–1650.

[51] Chen, Y., Abraham, A., Yang, J., and Yang, B. (2005)," Hybrid methods for stock index modelling. Proceedings of Fuzzy Systems and Knowledge Discovery", Second International Conference, 1067–1070.

[52] Dong, M., and Zhou, X. (2002),"Exploring the fuzzy nature of technical patterns of U.S. stock market", Proceedings of Fuzzy System and Knowledge Discovery, 1,324–328.

[53] Zhang, Y.-Q., Akkaladevi, S., Vachtsevanos, G., and Lin, T. Y. (2002)," Granular neural web agents for stock prediction. Soft Computing 6 406–431. https://doi.org/10.1007/s00500-002-0193-7.

[54] Zhang, D., Jiang, Q., and Li, X. (2004)," Application of neural networks in financial data mining", Proceedings of International Conference on Computational Intelligence, 392–395.

[55] Xueshen Sui, Qinghua Hu, Daren Yu, Zongxia Xie and Zhongying Qi, (2007),"A Hybrid Method for Forecasting Stock Market Trend Using Soft-Thresholding De-noise Model and SVM", Springer-Verlag Berlin Heidelberg, 387-394. https://doi.org/10.1007/978-3-540-72530-5_46.

[56] Swarnava Mitra and Atanu Das, (2009)," Security Index Forecasting Using Multi Step Ahead Wavelet Neural Network and Wavelet Garch A Comparative Study", Institute of Management Studies,4(2),17-21.

[57] Mahdi Pakdaman Naeini, Hamidreza Taremian and Homa Baradaran Hashemi, (2010)," Stock Market Value Prediction Using Neural Networks", International Conference on Computer Information Systems and Industrial Management Applications, 132-136.

[58] Victor Devadoss,A and Antony Alphonnse Ligori,T,(2013)," Stock Prediction Using Artificial Neural Networks", International Journal of Data Mining Techniques and Applications,2, 283-291. https://doi.org/10.1109/CISIM.2010.5643675.

[59] Yusuf Perwej and Asif Perwej, (2012)," Prediction of the Bombay Stock Exchange (BSE) Market Returns Using Artificial Neural Network and Genetic Algorithm", Journal of Intelligent Learning Systems and Applications, 2012, 108-119. https://doi.org/10.4236/jilsa.2012.42010.

[60] Mingyue Qiu and Yu Song, (2016)," Predicting the Direction of Stock Market Index Movement Using an Optimized Artificial Neural Network Model", PLoS ONE 11(5): e0155133. Doi: 10.1371/journal. pone.0155133.

[61] Makridou, G., Atsalakis, G.S., Zopounidis, C. and Andriosopoulos, K. (2013) 'Gold price forecasting with a neuro-fuzzy-based inference system', Int. J. Financial Engineering and Risk Management, 1(1), pp. 35–54. https://doi.org/10.1504/IJFERM.2013.053707.

[62] Guo Z, Wang H, Yang J and Miller DJ, (2015)," A Stock Market Forecasting Model Combining TwoDirectional Two-Dimensional Principal Component Analysis and Radial Basis Function Neural Network", PLoS ONE 10(4): e0122385. https://doi.org/10.1371/journal.pone.0122385.

[63] Shipra Banik, A. F. M. Khodadad Khan, and Mohammad Anwer, (2014)," Hybrid Machine Learning Technique for Forecasting Dhaka Stock Market Timing Decisions", Computational Intelligence and Neuroscience, Article ID 318524, https://doi.org/10.1155/2014/318524.

[64] Yonghui Dai, Dongmei Han,and Weihui Dai,(2014)," Modeling and Computing of Stock Index Forecasting Based on Neural Network and Markov Chain", The Scientific World Journal , Article ID 124523, https://doi.org/10.1155/2014/124523.

[65] Guo Z, Wang H, Liu Q andYang J, (2014),"A Feature Fusion Based Forecasting Model for Financial Time Series", PLoS ONE 9(6): e101113. Doi: 10.1371/journal. pone.0101113.

[66] Jie Wang,Jun Wang, Wen Fang, and Hongli Niu,(2016)," Financial Time Series Prediction Using Elman Recurrent Random Neural Networks", Computational Intelligence and Neuroscience Article ID 4742515, https://doi.org/10.1155/2016/4742515.

[67] Hongli Niu and Jun Wang, (2014)," Financial time series prediction by a random data-time effective RBF neural network", Soft Computing, 18,497–508. https://doi.org/10.1007/s00500-013-1070-2.

[68] Rout, A.K. et al.,(2015)," Forecasting financial time series using a low complexity recurrent neural network and evolutionary learning approach", Journal of King Saud University – Computer and Information Scienc https://doi.org/10.1016/j.jksuci.2015.06.002.

[69] Ina Khandelwal, Ratnadip Adhikari and Ghanshyam Verma,(2016)," Time Series Forecasting using Hybrid ARIMA and ANN Models based on DWT Decomposition", Procedia Computer Science 48, 173 – 179. https://doi.org/10.1016/j.procs.2015.04.167.

[70] Ritanjali Majhi , G. Panda, Babita Majhi and G. Sahoo,(2009)," Efficient prediction of stock market indices using adaptive bacterial foraging optimization (ABFO) and BFO based techniques", Expert Systems with Applications 36,10097–10104. https://doi.org/10.1016/j.eswa.2009.01.012.

[71] Peter Zhang (2003)," Time series forecasting using a hybrid ARIMA and neural network model", Neurocomputing, 50,159 – 175 https://doi.org/10.1016/S0925-2312(01)00702-0.

[72] Jatinder Kumar, Amandeep Kaur and Pammy Manchanda (2015)," Forecasting the Time Series Data Using ARIMA with Wavelet", Journal of Computer and Mathematical Sciences,6(8),430-438.

[73] Jatinder kumara and Mandeep kaur(2016)," Comparison of different wavelet-based statistical methods in banking sector",International Journal of Mathematical Archive-7(6),18-26.

[74] Rahib h. abiyev and , vasif hidayat abiyev(2012)," Differential evaluation learning of fuzzy wavelet neural networks for stock Price Prediction", Journal of Information and Computing Science Vol. 7, No. 2, 121-130

[75] Uduak A. Umoh and Alfred A. Udosen (2014),"Sugeno-Type Fuzzy Inference Model for Stock Price Prediction", International Journal of Computer Applications, 103(3), 1-12. https://doi.org/10.5120/18051-8957.

[76] Chang, P.-C., & Liu, C.-H. (2006)," A TSK type fuzzy rule based system for stock price prediction, Expert Systems with Applications, https://doi.org/10.1016/j.eswa.2006.08.020.

[77] Salim Lahmiri (2012),"Wavelet transform, neural networks and the prediction of S&P price index: a comparative study of back propagation numerical algorithms", Business Intelligence Journal, 592,235-244.