IMPROVING TIME SERIES MODELS PREDICTION BASED ON EMPIRICAL MODE DECOMPOSITION USING STOCK MARKET DATA

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by

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LIST OF SYMBOLS

α, β, γ	Smoothing parameters
ε_t	The random error at time t
u_e	Upper cubic spline envelope of EMD sifting process
l_e	Lower cubic spline envelope of EMD sifting process
$f(t)$	Forecast value of y at time t
h	Forecast horizon
λ_1, λ_1	Affine combination coefficients
m_e	Mean envelope of EMD sifting process
t	Discrete time
$x(t)$	Original time series data

LIST OF ABBREVIATIONS

ADF test	Augmented Dickey-Fuller Test
APTV	Aptiv PLC
AR	Autoregressive Methods
ARIMA	Autoregressive Integrated Moving Average
BKR	Baker Hughes Company
CAG	Conagra Brands, Inc.
CERN	Cerner Corporation
COO	The Cooper Companies, Inc.
DFT	Discrete Fourier transform
EMD	Empirical Mode Decomposition
FFT	Fast Fourier transform
HCA	HCA Healthcare, Inc.
HHT	Hilbert-Huang Transforms
IMF	Intrinsic Mode Function
ISRG	Intuitive Surgical, Inc.
KEY	KeyCorp
MA	Moving Average Methods
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scale Error
MSI	Motorola Solutions, Inc.
NRG	NRG Energy, Inc.
NTAP	NetApp, Inc.
RMSE	Root Mean Square Error
RMSRE	Root Mean Square Relative Error
RWD	Random Walk with Drift
SCHW	The Charles Schwab Corporation
sMAPE	Symmetric Mean Absolute Percentage Error

MENINGKATKAN RAMALAN MODEL SIRI MASA BERDASARKAN PENGURAIAN MOD EMPIRIK MENGGUNAKAN DATA PASARAN SAHAM

ABSTRAK

Analisis dan ramalan siri masa adalah bidang penyelidikan yang sangat penting dan aktif. Pada zaman penghasilan data yang banyak ini, penggunaan data yang ada dengan betul telah menjadi penting dalam ramalan dan membuat keputusan. Tesis ini mempersembahkan kajian penyelidikan yang melibatkan pembangunan lima kaedah ramalan lanjutan dan eksperimen pada dua belas set data siri masa harga saham. Kaedah peramalan tradisional mempunyai batasan dalam potensi ramalan kerana anggapan linear dan kepegunan pada set data. Walau bagaimanapun, data sebenar termasuk data harga saham mempunyai ciri dan corak canggih yang merangkumi tidak linear dan tidak pegun. Oleh itu, skop kajian adalah mencari kaedah yang lebih baik untuk meningkatkan ketepatan ramalan yang diperoleh daripada kaedah tradisional dengan menerapkan pendekatan lanjutan. Penguraian mod empirik (EMD), bahagian yang sangat penting dari transformasi Hilbert-Huang (HHT) adalah algoritma penguraian yang sangat mudah suai untuk melihat data dari butiran dan skala masa yang berbeza. Sebagai alat analisis yang teguh dalam pemprosesan isyarat, EMD telah banyak digunakan dalam bidang lain termasuk ekonomi dan kewangan. Walau bagaimanapun, masih terdapat ruang dalam meningkatkan ketepatan ramalan siri masa kewangan tidak linear tidak pegun menggunakan EMD dan kaedah ramalan lain. Berdasarkan hipotesis yang relevan, kajian ini diikuti oleh tiga objektif kajian. Lima kaedah berasaskan EMD dikembangkan pada objektif ini. Kaedahnya ialah EMD-Theta (EMD dengan kaedah Theta), Aff.EMD-EWMA1 (gabungan afin antara EMD-

EWMA dan EMD-ARIMA), Aff.EMD-EWMA2 (gabungan afin antara EMD-EWMA dan ARIMA), EMD-ARIMA -EWMA (EMD dengan ARIMA untuk komponen pegun dan EWMA untuk komponen tidak pegun) dan EMD-EWMA-ARIMA (EMD dengan EWMA untuk komponen pegun dan ARIMA untuk komponen tidak pegun). Di sini, ARIMA bermaksud purata bergerak bersepadu autoregresif dan EWMA adalah purata bergerak berwajaran eskponen. Prestasi ramalan kaedah-kaedah yang dicadangkan ini dinilai menggunakan dua belas set data pasaran saham dan prestasi mereka dibandingkan dengan lima kaedah perbandingan penanda aras iaitu ARIMA, EWMA, Theta, EMD-ARIMA dan EMD-EWMA menggunakan enam ukuran ralat. Ukuran ralat ini ialah RMSE, MAE, RMSRE, MAPE, MASE dan sMAPE. Hasil eksperimen menunjukkan bahawa kaedah yang dicadangkan menghasilkan ketepatan ramalan yang jauh lebih baik daripada kaedah asas yang dibandingkan. Oleh itu, kaedah berasaskan EMD yang mempunyai potensi prestasi lebih tinggi berbanding kaedah tradisional memerlukan perhatian penyelidikan lebih lanjut.

IMPROVING TIME SERIES MODELS PREDICTION BASED ON EMPIRICAL MODE DECOMPOSITION USING STOCK MARKET DATA

ABSTRACT

Time series analysis and prediction is a very important and active research area. In this age of profuse data generation, proper use of available data has become crucial in forecasting and decision making. This thesis presents the research study involving the development of five advanced forecasting methods and their experimentation on twelve stock price time series datasets. Traditional forecasting methods have limitations in forecasting potentiality due to their linearity and stationarity assumptions on the datasets. However, real life data including stock price data have sophisticated features and patterns encompassing nonlinearity and non-stationarity. Therefore, there is the research scope to search for better methods to improve forecast accuracy obtainable from the traditional methods by applying advanced approaches. Empirical mode decomposition (EMD), a very essentially important part of Hilbert-Huang transforms (HHT) is a very adaptive decomposition algorithm to view data from granular and different time scales. Being a robust analysing tool in signal processing, EMD has been widely applied in other fields including economics and finance. However, there are still scopes in improving the forecast accuracy of nonlinear nonstationary financial time series using EMD and other forecasting methods. From such relevant hypotheses, this study was followed by three research objectives. Five EMD-based methods were developed on these objectives. The methods are EMD-Theta (EMD with Theta method), Aff.EMD-EWMA1 (affine combination between EMD-EWMA and EMD-ARIMA), Aff.EMD-EWMA2 (affine combination between EMD-EWMA and ARIMA), EMD-ARIMA-EWMA (EMD with ARIMA for

stationary components and EWMA for nonstationary components) and EMD-EWMA-ARIMA (EMD with EWMA for stationary components and ARIMA for nonstationary components). Here, ARIMA stands for autoregressive integrated moving average and EWMA is for exponentially weighted moving average. The forecasting performance of these proposed methods were evaluated employing them on twelve stock market datasets and their performances were compared with five benchmark compared methods namely ARIMA, EWMA, Theta, EMD-ARIMA and EMD-EWMA using six error measures. These error measures are RMSE, MAE, RMSRE, MAPE, MASE and sMAPE. The experimented results show that proposed methods produced comparatively better forecast accuracy than the compared base methods. Therefore, EMD-based methods which have potentiality of outperformance over traditional methods deserve further research attention.

CHAPTER 1

INTRODUCTION

1.1 Preview of the Chapter

This introductory chapter depicts the overall research study in a nutshell. In section two, the background of the study is briefly and generally described. In section three, the research problem or main focus is presented in connection with the background study. In section four, three research objectives to contribute on the research problem are described. Scopes within and beyond but relevant to this study is presented in the section five. In section six, significance or importance of the study is briefly discussed. Limitations of the study are presented in section seven. The thesis organization is presented in section eight.

1.2 Background of the Study

A time series is a historical observations sequence of any event or collection of numeric data values that existed in time order. In many areas of knowledge and research domain, studies and practices related to time series have been prevalent (Chatfield, 2000). Concurrently, this active research area is extending by the contributions of researchers from different inter-related fields. Some works on time series research and practices are presented in (De Gooijer & Hyndman, 2006) and (Hyndman, 2020). This field of study is very important (Alhnaity & Abbod, 2020) and interesting as well as quite challenging. Many phenomena of reality are not completely random or uncertain rather their future shapes and patterns are intrinsically correlated with past and present events. The degrees of randomness are varied from data to data and domain to domain. In many cases, hidden or not-easily-detectable relations of future data with past and present data are ingrained. Such potentiality encourages research works and practices in this field. However, each data or event is different. Some events can be predicted relatively easily, whereas some events are pretty tricky and challenging to make prediction (Makridakis, 1986).

Financial time series being humanly involved have several factors of influence including economic, psychological and political factors in shaping asset pricing pattern (W. Huang et al., 2005) produce high fluctuation and randomness into series assets price (e.g., stock price). Thus, complex patterns in stock price make the task of prediction a tough and challenging one. However, stock prices should be informationally efficient according to the 1970 study of Fama (2021) related to efficient market hypothesis. Therefore, the use of historical or past stock price data for future price prediction can be useful and entirely relevant.

Essentially important task here firstly involves capturing of data characteristics, secondly, fitting those data by applying appropriate methods based on the data characteristics. Nowadays, many statistical, fuzzy theory based and machine learning models are used to forecast time series. Hybrid and combination methods are practiced, reflected and encouraged in many works. Among many directions and choices in time series forecasting, this study is focused on Empirical Mode Decomposition (EMD)-based methods for method selection and stock price data for data selection.

1.3 Problem Statement

There are already many statistical methods and method classes in time series forecasting which play important contributions in different related and relevant fields. These methods have merits and demerits. Also, they have foundational limitations. Therefore, there are research scopes to contribute in time series forecasting especially on the nonlinear nonstationary time series by developing advanced methods for better forecast accuracy. The major problems and limitations of the traditional methods are presented below:

1) Traditional or classical methods have the linearity assumption (Alhnaity & Abbod, 2020) of time series on which they can be employed. Therefore, they cannot capture the nonlinearity features of the data and they cannot forecast with full potentiality due to methodical limitation. In most cases, real life data (including stock market data) are nonlinear. Therefore, employing traditional methods in such cases may not be right choice.
2) Another limitation of the traditional statistical forecasting methods is the stationarity assumption (Alhnaity & Abbod, 2020), i.e., statistical properties of central tendency and dispersion measures will be invariant of time. The sameness or stationarity assumptions of these methods including constancy of mean, variance and autocorrelation is not practically feasible. Besides, different transformation and old decomposition techniques does not aid much in improving the forecast accuracy of the traditional methods.
3) Single methods are useful to same or similar type of data patterns. However, sophisticated data contain multiple constituents of different patterns which may not be easily visible and traditional methods may not capture such hidden properties. When these varied patterns are disintegrated with EMD and suitable

methods are applied on these components, the approach can be efficient and better forecast accuracy can be achieved.

4) In some cases, there may exist data noise in data which can significantly decrease the performance of forecasting methods. Traditional methods cannot solve this problem. In such cases, required denoising by using EMD can be effective.

1.4 Research Objectives

This research focuses on EMD-based nonlinear nonstationary time series forecasting and the application domain is stock market data. Started from three hypothetical viewpoints (which are stated below) in pursuit of better hybrid forecasting methods, this thesis is laid upon the following three objectives:

1) To develop an EMD-based hybrid method with a single statistical method that can outperform benchmark models and perform better than the existing EMD-based statistical hybrid methods EMD-ARIMA and EMD-EWMA.
2) To improve further the forecast results of stock datasets by applying combination methods like affine combination between the preferred EMD-based hybrid method and other better-performing methods.
3) To develop an EMD-based outperforming method by applying two statistical forecasting methods on the EMD components, i.e., one method for stationary components and another method for non-stationary components.

1.5 Scope of Study

The main focus of this study is developing EMD based methods to improve the forecast accuracy of sophisticated real-life data especially those which are nonlinear and nonstationary in nature. The thesis is on the three hypotheses and on the five proposed methods based these hypotheses. There might be other hypotheses and other possibilities of different methods beyond the scope of this and the current study. Also, domain of application is stock price data which is an important part of finance and economics. The used datasets being of daily data, they can be considered high frequency data. Although there can be other very high frequency data like minute data or hourly data which are beyond the scope of this study. However, these methods and techniques can be applied to other related and relevant field of study and practice.

1.6 Significance of the Study

There are many events in near or far future on which many individuals or organisations need to take decisions where data can be of time series genre. In many such cases, careful and effective use of historical and present data can be of much help to look into the potential future. To analyse and get the potentially insightful message through intrinsic patterns, firstly efficient analysing tools are required. After analysis or disintegration of apparently hidden information, better forecast accuracy can be made by applying effective and efficient methods. This study encompasses a very efficient, locally adaptive data analysis or decomposing algorithm EMD and employs statistical forecasting methods to improve benchmark results. This is true that forecasting future events which are entangled with high uncertainty is very much challenging and, in some cases, quite impossible. However, there are cases where there are trends and patterns in the historical data which can repeat in the future in the similar but might not in the same way. In those events, different analysing and forecasting tools can be used to aid the decision making. The stock market forecast accuracy is very important to different investors and traders including individual investors, institutional investors and mutual fund managers. Apart from analysing tools, forecasting methods are very practicable to any stock market researchers, market regulators and other decision-makers. Also, such study on EMD-based forecasting methods can help develop advanced forecasting technology which may include other advanced techniques in parallel.

1.7 Limitations

Although time series forecasting studies continuously try and look for better methods especially in time series forecasting, there are always limitations. Because, when a dataset is better captured by a particular method, it can be better forecasted by the method provided the future data follow the same pattern or it is not disturbed by external forces. However, there are countless cases when financial time series is adversely disturbed and pattern is modified or lost being completely noisy. In such cases, forecasting methods will not be of help. Therefore, not just EMD-based hybrid or combination methods, any method can fail to produce even satisfactory results if data has very less capturable pattern or very noisy. Financial time series frequently suffer from such reality. Beyond the limitations, there are cases when methods can produce outperforming accuracy among different competitive methods used in the same application setting.

1.8 Thesis Outlines

In chapter 1, the overview of this study is presented. In chapter 2, literature review related to this is done from two directions. One is in the context of the general time series forecasting research trend including financial and economic domain. Another is in the context of EMD-based time series forecasting. Also, related preliminaries of classical or basic forecasting theories, EMD-related theories and hybrid method are described. In chapter 3, five proposed methods (EMD-Theta, Aff.EMD-EWMA1, Aff.EMD-EWMA2, EMD-ARIMA-EWMA and EMD-EWMA-ARIMA) are presented. Chapter 3 also include the six forecast error measurement tools - Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Root Mean Square Relative Error (RMSRE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE) and Symmetric Mean Absolute Percentage Forecast Error (SMAPE). Chapter 4 presents description and analysis of datasets which also include descriptive statistics and line graphs of datasets, graphs of EMD components, their stationarity test p-values and brief description of the companies behind the stocks. Chapter 5 presents overall forecast results for datasets and for all methods proposed and compared expressed through the error measures. Also, important findings or results are separately presented in chapter 5. Chapter 6 discusses and explains the results and evaluates how the objectives are achieved through the proposed methods. Chapter 7 concludes with the key points of the research work along with potential future works.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter consists of eight sections. Section two presents forecasting research trend of time series in a nutshell (including statistical, fuzzy and genetic algorithm along with machine learning based methods). Section three presents brief overview and trend of hybrid methods and their developments. Section four briefly explores into the research works of time series in financial and economic domain. Section five reflects on the forecasting research studies involving EMD-based methods. Section six summarizes EMD-based forecasting research trend. Section seven conveys decomposition-based forecasting methods in time series. This section describes decomposition approaches based on basic components, LOESS (locally estimated scatterplot smoothing) of seasonality and trend, Fourier transforms, Wavelet transformations and particularly Hilbert-Huang Transforms (HHT) which contains EMD. Section eight includes classical base methods or benchmark methods specially methods founded up on autoregression and exponential smoothing. Section nine encompasses Theta method. Section ten describes EMD-based EMD-ARIMA and EMD-EWMA hybrid forecasting methods.

2.2 Research Trend in Time Series Forecasting

People have had conveyed curiosity of forecasting events for millennia (Hyndman & Athanasopoulos, 2018) for multifarious purposes. Furthermore, forecasting has become important in many domains of knowledge and application areas (Chatfield, 2000) in the modern world of enormous recorded data and statistics. There are three common types of models for a forecaster to choose, i.e., qualitative techniques, causal models and time series analysis based models (Chambers et al., 1971). Among these types, time series-based forecasting techniques rely on historical data patterns. Along with early developed Autoregressive (AR) method from work of Yule (1927), Moving Average (MA) method by Slutzky (1937), important classical time series methodological contribution was ARMA class from consequential works of Wold (1938) and Whittle (1951). ARMA class was further developed to ARIMA class as more generalized fitting and forecasting technique of time series with the contribution of Box et al.(2015) and Cholette(1982). Although ARIMA class is classical, it is still widely extant in research studies of different fields and forecasting applications involving time series due to its effective performance in forecasting. Some recent ARIMA-based works are Zhao et al. (2019) for predicting Kubernetes (a software for cluster management) resource, Jiang et al. (2018a) in forecasting coal consumption, investment and price of China by 2030, Alghamdi et al. (2019) on traffic congestion forecasting, Alsharif et al. (2019) for predicting solar radiation involving daily average as well as monthly average data for their South Korea's Seoul-based case study. Moreover, some other studies include Covid-19 forecasting of Hernandez-Matamoros et al. (2020), transportation price forecasting regarding full truckload of Miller (2019) and works of (Köppelová & Jindrová, 2019; L. Luo et al., 2017; Ohyver & Pudjihastuti, 2018) and (H. Liu et al., 2020, p. 2), all of which employed ARIMA class as forecasting tool.

Apart from ARIMA class, other widely practiced forecasting techniques involve exponential smoothing class. These exponential smoothing techniques started to develop from the rudimentary work of Brown (1957) which was conceptually originated from Denis Poisson's 17th century numerical analysis works dealing with exponential window as well as weighted average. This work of Brown (1957) contributed exponentially weighted moving average (EWMA) or simple exponential smoothing (SES). EWMA or SES was further developed and extended from single to double smoothing with the 1957 work of Holt (2004) reprinted in 2004 and to triple smoothing with the work of Winters (1960). Other important contributions on this exponential smoothing based forecasting techniques were one from the works of Gardner Jr (1985) and another from Gardner Jr (2006). Like ARIMA class, exponential smoothing class has good forecasting efficiency and therefore it is still enormously practiced. Recent smoothing methods-based works encompass Akpinar & Yumusak (2017) for day-ahead forecasting of natural gas as non-seasonal case, Tran et al. (2020) for cellular traffic forecasting and works of Köppelová & Jindrová (2019); Liu et al. (2020,), and Luo et al. (2017).

Many forecasting researches of time series are influenced by machine learning, fuzzy theory and genetic algorithms. Some of machine learning (including deep learning or neural network based) works are Waheeb & Ghazali (2019) for forecasting exchange rate, Alghamdi et al. (2019) for forex forecasting, Xiao et al. (2020) for short-term forecasting of wind speed, AlKandari & Ahmad (2020) for predicting solar power production, Liagkouras & Metaxiotis (2020) to forecast stock market data. Other works of similar methods encompass Meng & Khushi (2019); Samanta et al. (2019); Shen et al. (2020) and Larrea et al. (2020). From literature it is apparent that machine learning based forecasting studies frequently experiment with support vector machines (SVM), Random forest, artificial neural networks (ANN), multilayer perceptron (MLP), extreme learning machine (ELM), recurrent neural networks (RNN) which specially include long short-term memory (LSTM) and gated recurrent units (GRU), convolutional neural networks (CNN), Reinforcement Learning (RL) etc. For forecasting prices of coking coal, Matyjaszek et al. (2019) focused on ARIMA and neural networks; Ribeiro et al., (2019) focused on wavelet based neural networks for load forecasting, Singh & Huang (2019a) on neutrosophic set theory, ANN and gradient descent with stock index and enrolment data forecasting, Singh (2020) on neutrosophic-PSO method, Saâdaoui & Rabbouch (2019) on wavelet and neural network-based hybrid method for short-term price forecasting of electricity, Singh & Huang (2019b) on neutrosophic set based quantum optimization, Khashei & Hajirahimi (2019) on hybrid ARIMA-MLP methods comparison with stock price data. Furthermore, there are remarkable number of research studies involving Fuzzy theory, e.g., in stock data forecasting, Lah et al. (2019) used AR and fuzzy number, Tsai et al. (2019) experimented with multi-factor (three factors in their work) based fuzzy theory to predict stock indices, Prado et al. (2020) focused on ensemble method with ARMA, ANN, Fuzzy inference, adaptive neuro-fuzzy inference, SVM, ELM and genetic algorithm for long-term forecast of energy demand. It is well-known that machine learning especially deep learning methods are computationally expensive and also Makridakis et al. (2018a) reported disadvantages of machine learning methods over statistical methods as forecasting approaches. Beyond these machine learning based and fuzzy theory based forecasting related research trend, there are other distinct direction of time series research which include Song et al. (2019) on Brownian motion of fractional type, Deng et al. (2020) on Markov process with hidden state, Doğan & Midiliç (2019) on MIDAS method to forecast Turkish GDP growth, Hao et al. (2020) on robust regression using regularization constraints for predicting crude oil real prices, Leng & Li (2020) on Bayesian approach and Econophysics to forecasting prices of crude oil etc.

Useful and important time series literature on forecasting is finely sketched in the works of Hyndman (2020) and De Gooijer & Hyndman (2006) which convey the greatness of M3-competition winning Theta method along with other well-performing methods and techniques. Theta method originally developed by Assimakopoulos & Nikolopoulos (2000) involved or influenced the works of Hyndman & Billah (2003); Nikolopoulos et al. (2011); Nikolopoulos & Thomakos (2019); Spiliotis et al. (2019) and Thomakos & Nikolopoulos (2014).

Apart from simple-single and hybrid methods, the ensemble and forecast combinations methods are also applied and experimented in different research studies. M-competitions or Makridakis competitions have the important and reflective contributions in the field of forecasting with time series data. The works of Makridakis et al. (2020) and Makridakis et al. (2018b) summarized and reflected on the results and findings of M-4 competition. It showed that the majority (12 methods out of 17) of the accurate and winning methods were combination methods. In their work, Petropoulos et al. (2019) found that combination methods had superior performance over single benchmark methods. The studies of Pawlikowski & Chorowska (2020) revealed that their well-chosen weighted combination of statistical methods outperformed other methods and their submission positioned overall third rank in M-4 competition. The work of Kriz (2019) presented ensemble-based forecast methods which combine single methods and it also reported the overall better forecast results of used ensemble methods than compared single forecasts. Enunciation of Thomson et al. (2019) encompasses that combination of individual forecasts produces improvement in final forecast in the context of many forecasting practices. The paper of Petropoulos & Svetunkov (2020) described their median combination-based M-4 winning method which was comprised of four single methods. Illustration and interpretation of Atiya (2020) made efforts to cover the reasoning of forecast combination in generating better forecast results. Long before these recent works on forecasting combination, Clemen (1989) reviewed the then existing works along with a broad list of annotated bibliography. Also, according to Granger & Ramanathan (1984), linearly combined forecasts have the potentiality of outperforming single or individual forecasts; while the use of (generally positively) weighted average with total weight of unity is the common practice, their work considered three other alternative approaches which involve addition of constant term, non-unity weight sum and even the possibility of negative weights. Other forecast combination-based works slightly far from recent time include the work of Barrow & Kourentzes (2016) which focused on forecasting error distributions in forecast combinations and experimented on inventory data sets (weekly sales data) among others. Shaub (2020) also discussed on forecast combination approach which was one of the M-4 competition winners.

2.3 Hybrid Methods and Their Developments

In the research study of developing better or outperforming forecast methods, hybrid methods have been increasingly popular. Some researchers have focused on developing single methods which are better performing than conventional ones. However, it is found from majority of literature that hybrid methods generally and frequently outperform single methods. Some of the recent hybrid method-based studies are present in section 2.4 and 2.5. Conceptually, hybrid methods employ different single methods and effective strategies to capture different features of sophisticated data where single methods lay behind due to their foundational limitations. Hybrid methods have different research directions. The popular directions are machine learning and deep learning-based hybrid methods, fuzzy theory-based hybrid methods and decomposition-based hybrid methods including EMD-based methods. All of these methodical research directions involved diversified domain of application. Briefly, many research studies are contributing by developing hybrid forecasting methods and thus time series forecasting is moving forward.

2.4 Forecasting of Financial Time Series

Finance and economics are crucial part of modern world. With the speed of finance and economy, huge data are generated and further used for analysis and decision-making purpose. Many researchers as well as practitioners worked on forecasting with financial and economic time series data. These data encompass the sub-domains of stock, forex, cryptocurrency, commodity price and macroeconomic indicator data.

Research works on stock market index and stock price forecasting involved various methods. Review work of Henrique et al. (2019) focused on literatures which devoted to machine learning techniques and experimented for the prediction of financial market data. Sezer et al. (2020) reviewed deep learning-based time series literature in the time frame of 2005-2019 which involve forecasting in economic domain. Meng & Khushi (2019) focused on reinforcement learning and implemented the method using stock and forex data. In stock price, stock index and forex data forecasting, application of genetic algorithm with LSTM was the contribution of Huang et al. (2020). Using fractional neural network based ARFIMA-LSTM, Bukhari et al. (2020) forecasted stock price data. To forecast stock price data, Fernández et al. (2019) used linear predictor, extreme learning machine and discrete wavelet transform. For forecasting stock data, Yan & Zhao (2019) worked on improved CNN. Liagkouras & Metaxiotis (2020) used SVM to forecast stock price data of some FTSE-100 companies. In forecasting stock price data, Khashei & Hajirahimi (2019) experimented on comparative studies of ARIMA-MLP and MLP-ARIMA. Lah et al. (2019) applied AR (1) along with use of triangular fuzzy number and standard deviation to forecast stock market data of five different ASEAN countries (Malaysia, Philippines, Thailand, Indonesia and Singapore). For forecasting purpose, Tsai et al. (2019) developed fuzzy theory-based multi-factor fitting model and evaluated model performance by forecasting three stock index datasets (Nasdaq Stock Market, Taiwan Stock Exchange Index, and Hang Seng Index).

Using CNN-SVM method, Cao & Wang (2019) predicted stock index (Hang Seng Index). Qiu et al. (2020) forecasted S&P 500, Dow Jones Industrial Average (DJIA), Hang Seng Index datasets using attention mechanism (a type of wavelet transform) and LSTM. Two Chinese stock indexes (Shanghai Stock Exchange Composite Index and the Shenzhen Component Index) were forecasted by Dong et al.(2019) to implement learning-based model of data collection using search index (from Baidu.com). To develop forecasting method, Zhang et al. (2019) focused on SVR based firefly algorithm and implemented the method on stock price data. T.-L. Chen et al. (2019) worked on MLP regression and used seven indices where five from stock market indexes and remaining from gold and oil market. To experiment the method of fuzzy theory-based ANN, Singh (2018) used rainfall data and stock index data (Indian National Stock Exchange and Taiwan Stock Index Futures). Combined method of S. Sun et al. (2018) from LSTM and AdaBoost algorithm was implemented using four financial datasets (two from forex and remaining from stock index). Ertuğrul & Tağluk

(2018) experimented generalized method on behavioural learning on various financial datasets including stock indexes, forexes, financial futures and commodities. With the development of intuitionistic fuzzy theory-based forecasting method, Bisht & Kumar (2018) implemented the method on one stock price (state bank of India) and two stock indices (TAIEX and DJIA). For experimental purpose of hybrid wavelet-based ANN method, Bozic & Babic (2018) used forex rate data of Euro against Serbian dinar

Foreign exchange rate or forex related forecasting is important for traders, investors and related decision makers. There are many researches works in this area which dedicated to different methods and techniques. Two daily forex data sets (Japanese Yen/USD and Euro/USD) were used in the work of Waheeb & Ghazali (2019) which involve GA–TPFLNN method where TPFLNN is short form for tensor product functional link neural network. Ni et al. (2019) forecasted on nine forex datasets using RNN and CNN based C-RNN method. A method based on deep-learning and event-sentiment by Yasir et al. (2019) used to forecast three forex rate datasets (PKR/USD, GBP/USD and HKD/USD where PKR, GBP and HKD stand for Pakistani Rupee, British pound sterling and Hong Kong Dollar respectively). For experimentation of GA and PSO based SVR methods, Fu et al. (2019) forecasted four Chinese renminbi RMB or CNY forex rates against USD, EUR, JPY and GBP. Raimundo & Okamoto (2018) focused on SVR-DWT where DWT stands for discrete wavelet transform and experimented the method on forex data.

Now-a-days cryptocurrencies are getting increased attention of traders and investors and these digital currencies have a high future potentiality. Relevantly, many researches dedicated in this area for forecasting using different methods. The work of

X. Sun et al. (2020) involved trend forecasting for cryptocurrency price using LightGBM where GBM stands for Gradient Boosting Machine. To forecast bitcoin price, Atsalakis et al. (2019) focused on ANN and fuzzy-based forecasting techniques. To make forecast on widely traded cryptocurrencies (namely Bitcoin, Litecoin and Ethereum), Christoforou et al. (2020) used different ANN methods and compared results.

Commodity markets play crucial roles in business and commence. But like capital markets and money markets, commodity markets are also volatile and have potential time series pattern which attracted different researchers' attention. To forecast price, consumption and investment of China's coal by 2030, Jiang et al. (2018b) worked on ARIMA method. Miller (2019) used ARIMA method for forecasting transportation prices of full truckload. The work of Ohyver & Pudjihastuti (2018) involve rice price forecasting using ARIMA method. Using ARIMA and ANN, Matyjaszek et al. (2019) focused on coal price forecasting. K. Nikolopoulos et al. (2011) used theta method in supply chain forecasting for planning purpose. To forecast electricity price, Saâdaoui & Messaoud (2020) worked on wavelet and ANN based hybrid method. The hybrid method of Deng et al. (2020) by integrating hidden Markov model with dynamic time wrapping was used for forecasting crude oil market data. Hao et al. (2020) forecasted crude oil price data applying robust regression methods which involve regularization constraints. The work of Leng & Li (2020) used Bayesian theory and Econophysics approach to forecast crude oil price. To forecast gold price data, Livieris et al. (2020) focused on hybrid CNN-LSTM method. Using Bayesian-network based hybrid method, Fazelabdolabadi (2019) forecasted crude oil price. Dagar et al. (2018) focused on ELM-

AE where AE is for auto-encoder and experimented the method on two price data time series (gold and crude oil).

Among forecasting researches on financial time series, there are works on GDP data. For Turkish GDP growth forecasting, Doğan & Midiliç (2019) used mixed data sampling method or briefly MIDAS method. For GDP forecasting of four Scandinavian countries (Denmark, Finland, Norway and Sweden), Claveria et al. (2019) focused on evolutionary computation method (especially genetic algorithms).

There are also EMD-based financial forecasting related research works which encompass stock price, stock market, forex rate, cryptocurrency price, commodity price, macroeconomic indicator data. Akin to other research areas, stock market index and stock price forecasting related researches involve different methods and approaches.

EMD-based financial forecasting methods are basically hybrid methods with other statistical, machine learning and fuzzy theory-based methods. For forecasting Taiwan CSR or corporate social responsibility index data, S.-L. Lin & Huang (2020a) worked on hybrid EMD-LSTM method. J. Wang & Wang (2017) forecasted four stock indexes (FTSE, NYSE, HIS and DAX) using hybrid EMD–STNN where STNN stands for stochastic time strength neural network. The research study of L. Chen et al. (2019) forecasted SSE Index data using hybrid EMD-LSTM-ATTE where LSTM-ATTE stands for attention-based LSTM. Using HHT and machine learning methods (SVM, LSTM and regression tree ensemble), Leung & Zhao (2020) forecasted time series of S&P 500 index, the VIX volatility index of CBOE or Chicago Board Options Exchange, the gold price ETF or exchange-traded fund and treasury yield of 10-year period. In the work of Cao et al. (2019) combined CEEMDAN with LSTM to forecast stock indices (S&P500, HSI, German DAX and Chinese SSE or Shanghai Stock Exchange). The research study of Nava et al. (2018) involved hybrid EMD-SVR method which was experimented with intraday S&P500 Index. To forecast TAIEX Stock Index data, R. Yang et al. (2018) used hybrid method of fuzzy theory and EMD. A. Lin et al. (2012) focused on hybrid EMD–KNN method where KNN is abbreviated for k-nearest neighbors and for performance evaluation, the model was experimented on four stock indices (Singaporean STI, NYSE based NYA index, Dow Jones DJI index and HSI). Applying CEEMDAN-SVR method, Jothimani & Yadav (2019) forecasted the weekly closing price of Indian Nifty index constituents. By developing integrated predictive system with intrinsic mode functions (IMF), ANN and genetic algorithms (GA), Lahmiri (2020) focused on forecasting intra-day index data of S&P500.

Like other areas, EMD-based forex rate forecasting researches also involved neural networks and fuzzy theory. To forecast forex rates for Chinese RMB against USD, J.-N. Wang et al. (2019) used EMD-MLP hybrid method. In USD to Czech Koruna forex rate forecasting, Nghien et al. (2017) used HHT and fuzzy theory. The research work of H.-L. Yang & Lin (2017) forecasted four forex datasets (USD/TWD, GBP/TWD, AUD/TWD and EUD/TWD) using EMD-PSR-ELM method where PSR is brief form of phase space reconstruction.

Researches on commodity market data also involved EMD-based hybrid forecasting methods. Crude oil price time series data were forecasted using hybridization of CEEMDAN with ridge regression by T. Li et al. (2019). X. Qiu, Suganthan, et al. (2017) worked on EMD and ensemble kernel machine hybrid technique to forecast electricity price.

Besides, stock index, stock price, forex rate and cryptocurrency prices, there are also other economic and financial data which got research attention. Several of them are presented here. To forecast daily occupancy in hostels, G. Zhang et al. (2017) used EEMD-ARIMA method. The research study of Bedi & Toshniwal (2018) reflected on hybrid EMD-LSTM to forecast electricity demand. EMD-PSO-SVM method was used in the work of Da Silva et al. (2017) for demand data forecasting. The work of B. Zhu et al. (2017) focused on carbon price forecasting using EMD, GA and least squares SVR based hybrid method. Shao-Jiang et al. (2018) focused on integrated EMD-BP method and implemented it in tourist number forecasting for Chinese Jiuzhaigou region. To forecast metro passenger flow, Q. Chen et al. (2019) used EMD-LSTM method.

2.5 EMD-based Forecasting Methods

EMD which was primarily devised to serve signal analysis later involved time series forecasting with hybrid methods. These methods are constructed integrating different statistical, regression, machine learning, deep learning, fuzzy theory-based and other potential genre of methods. EMD-based statistical hybrid methods involve several statistical methods. The work of G. Zhang et al. (2017) showed that EEMD-ARIMA have potentiality for forecasting accuracy improvement of widely used ARIMA method. The wind speed forecasting related work of Yu et al. (2017) revealed that considering short-term forecast results EMD-ARMA performed better than traditional ARMA method. The proposed EMD-SARIMA method of Nai et al. (2017) produced better result in air traffic forecast than Naïve, SARIMA and Holt–Winters methods. In the work of Awajan et al. (2018), proposed EMD-HW bagging and experimented it in forecasting stock market data which produced better accuracy than other compared methods. For streamflow forecasting, Z.-Y. Wang et al. (2018) reported the outperformance of EMD-ARIMA over ARIMA and EEMD-ARIMA.

Some EMD-based hybrid forecasting methods were integrated with robust regressions. As per the experimental results in the work of T. Li et al. (2019), proposed ICEEMDAN-DE-RR (where ICEEMDAN, DE and RR stands for improved CEEMDAN, differential evolution and ridge regression respectively) better performed than other compared approaches. Naik et al. (2018) found that EMD-WKRR (where WKRR stands for wavelet kernel-based ridge regression) hybrid method exhibited superior forecast results of wind speed as well as wind power over other compared methods.

With the increased popularity and application of artificial intelligence and machine learning algorithms, there are abundant machine learning-based forecasting researches some of which involve EMD-based hybrid methods. The research study of Z. Liu et al. (2019) presented that the hybrid EMD-LSSVR&QES (where QES is short form of quadratic exponential smoothing) method showed outperformance in forecasting over five other methods in their work. Nava et al. (2018) showed the outperformance of EMD-SVR over benchmark methods in forecasting financial time series. Hybrid EMD-PSO-SVM method in the work of Da Silva et al. (2017) showed superior performance over compared methods specially PSO-SVM method. Proposed EMD–LSSVR–ADD hybrid method of B. Zhu et al. (2017) produced better accuracy than other methods used in their work for carbon price forecasting. According to A. Lin et al. (2012), results of proposed hybrid EMD–KNN method were more accurate in stock price prediction than ARIMA and KNN method. The work of X. Zhao et al. (2017) presented that hybrid EMD-CLSSVM (where CLSSVM stands for chaotic LSSVM) model outperformed CLSSVM hybrid model. Proposed EMD-SVR integrated method in the study of Yaslan & Bican (2017) outperformed SVR method in forecasting with electricity load data. In forecasting of electricity price data, X. Qiu, Suganthan, et al. (2017) presented that their proposed hybrid EMD-KRR-SVR method best performed among other methods they used. Experimenting on solar power data, Majumder et al. (2017) found that EMD-ELM hybrid method produced better forecast accuracy than ELM. From their research study, H.-L. Yang & Lin (2017) reflected that EMD-PSR-ELM yielded better accuracy than single naive random walk, ARIMA, BPNN and ELM as well as hybrid PSR-ELM and EMD-ELM methods. As per experimental results of Fan et al. (2017), EMD-PSO-GA-SVR hybrid approach outperformed other forecasting methods they used.

Like EMD-based machine learning hybrid methods, many researches focused on EMD-based neural network or deep learning hybrid methods. Büyükşahin & Ertekin (2019) showed that their hybrid EMD-ANN method produced better forecasting accuracy than the accuracy found from traditional hybrid and other individual methods used in their research study. The work of Jothimani & Yadav (2019) reported the outperformance of CEEMDAN-SVR hybrid methods over single methods ANN and SVR as well EMD-based hybrid methods EMD-ANN, EEMD-ANN, CEEMD-ANN, EMD-SVR and EEMD-SVR. Polar motion prediction accuracy of ELM method was improved by Lei et al. (2017) using EMD-ELM for short-term as well as long-term. S.-L. Lin & Huang (2020b) presented in their financial data forecasting that hybrid EMD-LSTM improved the forecast accuracy of LSTM. In their research study, Cao et al.

(2019) found the forecasting supremacy of CEEMDAN-LSTM over single LSTM, SVM, MLP and other hybrid methods. The proposed method of S. Zhang et al. (2020) which integrated 3D CNN with EEMD performed better than other methods and in this work, EEMD even improved the forecasting accuracy of 3D CNN. Leung & Zhao (2020) focused on HHT (of which EMD is an essential part) based machine learning integrated methods involving regression tree ensemble, SVM, LSTM and compared their forecasting performance. The proposed EMD-STNN of J. Wang & Wang (2017) outperformed BPNN, STNN and SVM in financial time series forecasting. J.-N. Wang et al. (2019) proposed EMD-MLP hybrid methods and compared results among its class models (e.g. MLP (3), MLP (5), MLP (5,3), MLP (6,4) and corresponding EMD-based hybrid methods) for different horizons. The study of Büyükşahin & Ertekin (2019) proposed an ARIMA-ANN hybrid method which was further improved using EMD and these methods better forecast accuracy than traditional hybrid and other compared individual methods. Saâdaoui & Messaoud (2020) focused on EMD-based Neural ARDL (where ARDL stands for Autoregressive Distributed Lag) methods and compared results with benchmark models. In their work related to forecast of electricity demand data, Bedi & Toshniwal (2018) used EMD-LSTM hybrid method which outperformed RNN, LSTM and EMD-RNN for the experimented data. The EMD-LSTM-ATTE hybrid method of L. Chen et al. (2019) produced better results as compared to other methods in their financial data forecasting. For hourly power consumption predication, Dedović et al. (2018) used EMD-based ANN hybrid method which produced efficient results. In their study, Zou & Zhang (2017) worked on hybrid method EMD and LSSVR for load forecasting. To forecast air quality indices, two EMD based hybrid methods were proposed by S. Zhu et al. (2017) where one is EMD-SVR-Hybrid and another is EMD-IMFs-Hybrid and these methods were found superior to single ARIMA, GRNN, SVR methods and hybrid Wavelet-SVR, Wavelet-GRNN and EMD-GRNN methods. Using EMD-ARMA/Grey wave hybrid method, Y. Chen et al. (2020) produced better accuracy than compared methods random walk, ARMA and EMD-ARMA.

In the integrated system of intrinsic mode functions (IMFs), ANN and genetic algorithms (GA), Lahmiri (2020) found that EMD-GA-ANN performed superior over WT-GA-ANN as well as GA-GRNN where GRNN stands for general regression neural network. The research study of Agana & Homaifar (2018) proposed EMD-DBN (where DBN stands for deep belief network) hybrid method which outperformed single DBN, MLP, SVR methods and hybrid EMD-DBN, EMD-MLP and EMD-SVR methods in drought forecasting. In their work related to sunspot number prediction, Lee (2020) presented that their proposed EMD-LSTM hybrid method produced better prediction accuracy. EMD-DBN hybrid method of X. Qiu, Ren, et al. (2017) achieved better forecast accuracy than single SVR, ANN, DBN, RF, EDBN methods and hybrid EMD-SVR, EMD-RF and EMD-SLFN methods with load demand data, where SLFN stands for single-hidden layer feedforward neural network. H.-F. Yang & Chen (2019) developed and investigated on hybrid EMD–SAE (where SAE stands for stacked auto-encoders) method and compared its superior results with other methods. For tourist number forecasting of Chinese Jiuzhaigou region, Shao-Jiang et al. (2018) used EMD and neural network based EMD-BP hybrid method. Applying EMD-ARG-LSTM (where ARG stands for adaptive regrouped) integrated method, Y. Li et al. (2018) found better prediction accuracy with cargo throughput data. Experimented with wind speed data in the work of Niu et al. (2017), proposed EMD-FOA-GRNN hybrid method (where FOA stands for optimized by the fruit fly optimization algorithm and GRNN for