A HYBRID EMD-MA FOR FORECASTING STOCK MARKET INDEX

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Abstract. Nowadays, stock market data forecasting has drawn a high attention in the field of nonstationary and nonlinear time series data with a high heteroscedasticity, since improving the forecasting accuracy is a hot topic for the researchers. Therefore, in this article the authors are proposed a new methodology via combining Empirical Mode decomposition and Moving Average model as a modified method to improve forecasting accuracy in content of stock market data. The strength of this proposed methodology lies in its ability to forecast nonlinear and non-stationary financial data without a need to use any transformation method. Moreover, this method provides a better model with sufficient forecasting accuracy. The daily stock market data of fourteen countries is applied to show the forecasting performance of the proposed method. Based on the five forecast accuracy measures, the results indicate that proposed forecasting method performance is superior to four selected forecasting techniques.

Keywords: Stock market index forecasting, Nonlinear and non-stationary time series, Empirical mode decomposition, Combined forecasting Model, Heteroscedasticity time series.

In financial time series analysis, one of the primary issues is modeling and forecasting financial time series data specifically stock market index. Usually, the transformation of a financial time series, rather than its original scale, is taken for describing its dynamics. Proper transformation is necessary to convert original non-stationary processes to stationary processes and subsequently to utilize mathematical and statistical properties for stationary processes. The hybrid models combine strengths of few traditional models to get a better forecasting accuracy. Recently, several hybrid models were applied EMD in the literature for time series forecasting. That by using EMD to decompose the non-stationary and non-linear time series data into Intrinsic Mode Functions (IMFs) and residual components. And then use forecasting model to forecast

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each component. Then all these forecasted values were aggregated to produce the final forecasted value of the original time series. Such as in [1] used a hybrid EMD-ARIMA (Autoregressive integrated moving average) to forecasting the monthly prices of rice data. Also, [14] also used the same methodology, but with wind speed data. A hybrid EMD-AR (Autoregressive) model was developed by coupling an AR model with the EMD technique in [8]. A hybrid EMD-LSSVR (least squares support vector regression) forecasting models has been applied on foreign exchange rate in [15]. While in [22] used a hybrid of EMD, LS-SVM (Least Squares-Support Vector Machines) and AR model with Kalman filter to predict wind speed data.

Therefore, the significant of this research article can be summarize as after intensive research in the financial forecasting literature, there are plenty research papers have been conducted in forecasting in content of stock market data such as [3], [2] and [12], also most of the articles have used the mentioned models directly without any combination such as [25].

With regard to all those literature reviews, this study attempts to employ the proposed method to forecast the daily stock market data of fourteen countries. Four selected forecasting models are used in the proposed method comparison to assess its performance of forecasting. Experimental results show that the proposed method is superior to existing method in terms of five accuracy forecasting measure. Section 2 introduces methods are used in methodology in this paper which are EMD, IMF and Moving Average Model. In this section introduces statistical techniques for consideration method. Section 3 presented the proposed methodology. Section 4 analyzes the daily stock market time series data of four countries with a discussion the result showing the capability of proposed forecasting method. Finally, in Section 5 some concluding remarks are addressed.

1. Methodology

In this section, the various steps for the implementation of the proposed forecasting method are described in detail. Which are Empirical Mode Decomposition, Moving Average Model and statistical techniques for consideration method.

1.1 Empirical mode decomposition (EMD)

EMD was described by [10], and this method has been modified by [16] and [13].The main idea of EMD is the decomposing of nonlinear and non-stationary time series data into several of simple time series. And it analyzing time series with keeping the time domain of the signal. It supplies an strong and adaptive process to decompose a time series into a combination of time series that known as intrinsic mode functions (IMF) and residual. Later, the original signal can be constructed back as the following:

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r(t) \tag{1.1}$$

where $x(t)$ represents the original time series, $r(t)$ represents the residue of the original time series data decomposition and IMF_i represent the i^{th} intrinsic mode function (IMF) series.

In order to estimate these IMFs, the following steps should be initiated and the process is called the sifting process of time series $x(t)$ [20] are shown below:

1. Start the first step by taking the original time series $x(t)$ for sifting process and assuming the iteration index value is $i = 1$.
2. Then, evaluate all of local extrema values of the time series $x(t)$.
3. After that, form the local maxima (local upper) envelope function $u(t)$ by connecting all local maxima values using a cubic spline line. In a similar way, form the local minimum (local lower) envelope function $l(t)$, and then form the mean function $m(t)$ by using this following

$$m(t) = \frac{u(t) + l(t)}{2} \tag{1.2}$$

4. Next, define a new function $h(t)$ using the mean envelope $m(t)$ and the signal $x(t)$ on this formula

$$h(t) = x(t) - m(t) \tag{1.3}$$

Check the function $h(t)$ is an IMF, according to IMF conditions (shown in the second part of this section). If the function $h(t)$ has satisfied IMF conditions, then go to step 5. If not, go back to step 2 and renew the value of $x(t)$ such that became $h(t)$, repeat steps 2 again until 4.

5. In step 5, firstly save the result of the IMF obtain from the last step. Secondly, renew the iteration index value such that became $i = i + 1$. Thirdly attain the residue function $r(t)$ using the IMF and the signal $x(t)$ on the formula

$$IMF_i(t) = h(t) \Rightarrow r_{i+1}(t) = x(t) - IMF_i(t). \tag{1.4}$$

6. Finally, make a decision whether the residue function $r(t)$ that acquire from step 5 is a monotonic or constant function. Then, save the residue and all the IMFs obtained. If the residue is not monotonic or constant function, return to step 2.

The steps 1 to 6 which were discussed above allow the sifting process (EMD algorithm) to separate time-altering signal features.

1.2 Intrinsic Mode Function (IMF)

Based on the EMD algorithm presented in the previous section, the IMF produces by the sifting process need to satisfy two conditions [20] which are

$$|Num[extreme] - Num[cross - zero]|<1. \tag{1.5}$$

where Num.extreme represents the number of local extreme points (all local maxima and all local minima), also Num[cross-zero] represent the number of cross-zero points

$$|m(t)| = |\frac{u(t) + l(t)}{2}|<\varepsilon, \tag{1.6}$$

where $u(t)$ represents the envelope function generated by using cubic spline line on all local maxima, $l(t)$ represents the envelope function generated by using a cube spline line on all local minima, $m(t)$ represents the mean function that it was obtained by evaluating the mean of $u(t)$ and $l(t)$, and ε is a very small positive number that close to zero, sometime equal zero.

1.3 Moving Average Model (MA)

A moving-average model is a model of linear regression uses past errors of the time series to describe the present observation. The moving average model of order q is denoted by $MA(q)$. Mathematically; $MA(q)$ of time series X_t is formally given by [7]:

$$X_t = \mu + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{1.7}$$

where μ is the mean of the series, and θ_1, ..., θ_q are the parameters may be positive or negative. And the ε_t,ε_{t-1},..., ε_{t-q}, are white noise error terms. The value of q is called the order of the MA model. This can be written using the backshift operator B as

$$X_t = \mu + (1 + \theta_1 B + \cdots + \theta_q B^q)\varepsilon_t. \tag{1.8}$$

The maximum of order q is selected by using the autocorrelation function(ACF) (see [23]). And the parameters θ_1, ..., θ_q are selected by using the Corrected Akaike's information criterion ($AICc$) by [11].

1.4 Statistical techniques for consideration method

In this study the proposed forecasting method is compered with four methods. Moving Average model, Holt-winter model was presented in [9] and [24], ARIMA models were presented in [18] and Random Walk method are used in order to validate the forecasting performance of proposed forecasting model.

These statistical methods were selected based on their performance in forecasting competitions and other empirical applications, as well as on their ability to capture salient features of the data. ARIMA (autoregressive integrated moving average) or Box-Jenkins models are generally denoted ARIMA(p, d, q). Where parameters p, d, and q are non-negative integers, p is the order of the Autoregressive model, d is the degree of differencing, and q is the order of the Moving-average model. Recently ARIMA is employed in several of studies in forecasting financial time series such as [4]. He applied ARIMA to forecast the cultivated area and production of maize in Nigeria.

A random walk (RW) is a process where the current value of a variable is composed of the past value with adding an error term defined as a white noise. It was first studied several hundred years ago as models for games of chance. Recently, In [17] have been shown that the random walk model turns out to be a hard to beat benchmark in forecasting the CEE exchange rates. And in [21] was applied a variable drift term with the random walk process. This was estimated using a Kalman filter. This simple statistical process was shown to perform better than all the three models that he was selected in out of-sample forecasts.

2. Propose methodology and data

In this section, the various steps for the implementation of the proposed forecasting method are described in detail. Which are Empirical Mode Decomposition and Moving Average Model.

2.1 Data

In this study, nonlinear and non-stationary time series data from the daily stock market of fourteen countries are used. These countries are Australia, Denmark, Estonia, Finland, France, India, Lithuania, Malaysia, Netherlands, Norwegian, Slovenia, Switzerland, Thailand and UK. While Figure 4 shows the time series plot of these countries. Table 1 presents these countries with the Basic statistics for each country, where S.Deviation is Standard Deviation, Nimf the number of IMFs and N is Number of observations. Moreover, Table 1 presents the p-value of KPSS (Kwiatkowski-Phillips-Schmidt-Shin by [5]), RESET (Ramsey Regression Equation Specification Error Test by [19]), BP (Breusch-Pagan test by [6] for nonstationary, nonlinear and heteroscedasticity, respectively. According to this value all stock market are significantly nonlinear, nonstationary with high heteroscedasticity. The data are extracted from the Yahoo finance website. The daily closing prices are used as a general measure of the stock market over the past six years. The whole data set - for each country - covers the period from 9 February 2010 to 7 January 2016. The data set is divided into two parts. The first part (m observations) is used to determine the specifications of the models and parameters. The second part, on the other hand, (h observations) is reserved for out-of-sample evaluation. This part is used comparison of performances among various forecasting models. Malaysia stock market data are taken as example. Where the number observation is N= 1459, the first part is m = 1458, 1457, 1456, 1455, 1494 and 1493 and the second part is h=1, 2, 3, 4, 5 and 6 respectively, are used.

2.2 Propose Methodology

The proposed methodology consists of four stages. Before began the proposed method, the time series data were divided into two parts. The first part is the training part to train the proposed method. This part is used to modeling to get the forecasting value of time series. The second part is the testing part. This part is used to compering with the forecasting value. After that, the time series are ready to follow this stage:-

1. Firstly, the use of empirical mode decomposition (EMD) on the time series. In this stage, the several Intrinsic Mode Functions (IMFs) and residue are obtained.

2. Secondly, the KPSS test [5] is applied on each of IMFs and residue to select the order of difference (d). While each component has own d. ACF is applied on all component to select the order of moving average model (q). If q of time series goes to infinity, the d is exceeded until q be finite. After that, the θ_1, ..., θ_q are selected by using the Corrected Akaike's information criterion ($AICc$) for each component.

3. Thirdly, by using the result p, q and θ_1, ..., θ_q - were found in the last stage - each component is modeling by $MA(q)$ to forecasting h days ahead.

4. Finally, in the this stage all the forecasting results for IMFs and residue are added up to get the forecasting for the time series.

After that the forecasting results are compared with the forecasting result of random-walk with draft, Holt-winter, ARIMA and moving average model without EMD. Figure 2 summarizes all the proposed methodology steps.

3. Result and discussion

In this study, stock market data of fourteen countries are used to present the forecasting accuracy of the proposed forecasting method. Four Models are used in order to validate the forecasting performance of proposed forecasting method. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error(MASE) and Theil's U-statistic (TheilU) will be utilized to evaluate the forecasting accuracy for each method. Equations 3.1, 3.2, 3.3, 3.4 and 3.5 are showed the formula of RMSE, MAE, MAPE, MASE and TheilU respectively. Where $\widehat{y_i}$ is the forecast value of the variable y at time period i from knowledge of the actual series values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}, \tag{3.1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}|, \tag{3.2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{y_i}|}{y_i}.100\%, \tag{3.3}$$

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y_i - \widehat{y_i}|}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}\right), \tag{3.4}$$

$$TheilU = \frac{\sqrt{\sum_{i=1}^{n-1}\left(\frac{\widehat{y}_{i+1} - y_{i+1}}{y_i}\right)^2}}{\sqrt{\sum_{i=1}^{n-1}\left(\frac{y_{i+1} - y_i}{y_i}\right)^2}}. \tag{3.5}$$

Table 2, 3, 4, 5, 6, 7 and Table 8 presented the comparison results of applied proposed forecasting method with four forecasting methods on Australia with Denmark, Estonia with Finland, France with India, Lithuania with Malaysia, Netherlands with Norwegian, Slovenia with Switzerland and Thailand with UK, respectively. When each table presents the result of five measure error for forecasting at h =1, 2, 3, 4, 5 and 6 days ahead. When the four forecasting methods are used to compare with proposed forecasting method. These methods are Holt-winter,moving average, ARIMA and random-walk with draft. The five error measures of RMSE, MAE, MAPE, MASE and TheilU are used to find the forecasting accuracy. The results obtained indicates that the forecast accuracy for proposed forecasting method (denoted by EMD-MA) is generally better than the four selected forecasting models.

4. Conclusion

In this article, the forecasting accuracy has improved in financial time series area since the forecasting accuracy still remains as one of the most difficult area due to the non-stationary and non-linear data. In this study, a new hybrid method has composited which are EMD and MA for modeling and improving forecasting accuracy in content of stock market data for fourteen countries based on several comparison forecast accuracy measurements. Then the findings indicate that proposed is able to outperform the four forecasting models. Thus, this paper has strengthened the idea that proposed forecasting method is suitable for stock market data. These results which will be useful to predict the future event and some structure breaks event.

Table 1: Basic statistics of time series

Country	Mean	Median	SD	Skewness	Kurtosis	N. IMF	N	KPSS p.value	RESET p.value	BP p.value
Australia	4928.42	4939.35	483.66	0.03	-1.05	7	1498	$<.01$	$<.01$	$<.01$
Denmark	586.71	519.34	197.16	0.84	-0.52	7	1466	$<.01$	$<.01$	$<.01$
Estonia	726.91	759.33	112.62	-0.27	-1.29	7	1471	$<.01$	$<.01$	$<.01$
Finland	2554.56	2455.44	474.05	0.39	-0.88	7	1476	$<.01$	$<.01$	$<.01$
France	3968.26	3939.82	557.54	0.21	-0.6	7	1516	$<.01$	$<.01$	0.268
India	20964.54	19501.08	4045.57	0.73	-0.94	6	1465	$<.01$	$<.01$	$<.01$
Lithuania	399.79	400.22	61.73	0.02	-1.26	6	1460	$<.01$	$<.01$	$<.01$
Malaysia	1638.2	1643.89	164.52	-0.4	-0.68	7	1459	$<.01$	$<.01$	$<.01$
Netherlands	370.77	355.92	56.19	0.65	-0.32	6	1516	$<.01$	$<.01$	$<.01$
Norwegian	591.02	581.59	97.87	0.05	-0.99	8	1476	$<.01$	$<.01$	$<.01$
Slovenia	710.01	703.86	107.07	0.06	-1	6	1438	$<.01$	$<.01$	$<.01$
Switzerland	7375.98	7226	1191.92	0.08	-1.41	8	1508	$<.01$	$<.01$	$<.01$
Thailand	1254.45	1300.22	247.91	-0.42	-0.94	7	1442	$<.01$	$<.01$	$<.01$
UK	6114.4	6059.3	538.36	-0.15	-1.09	8	1528	$<.01$	$<.01$	$<.01$

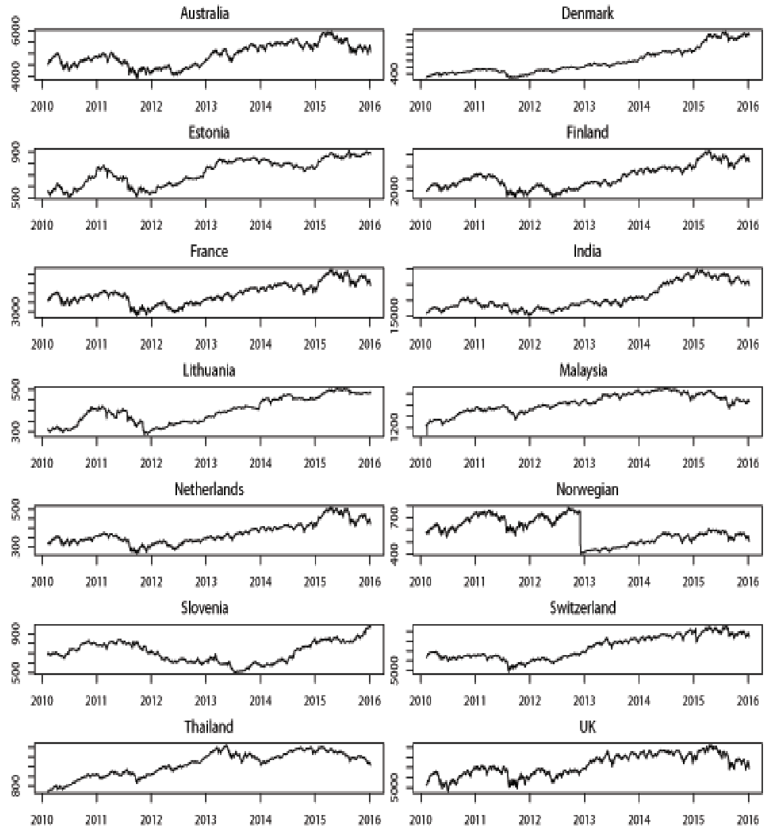

Figure 1: Time series plot

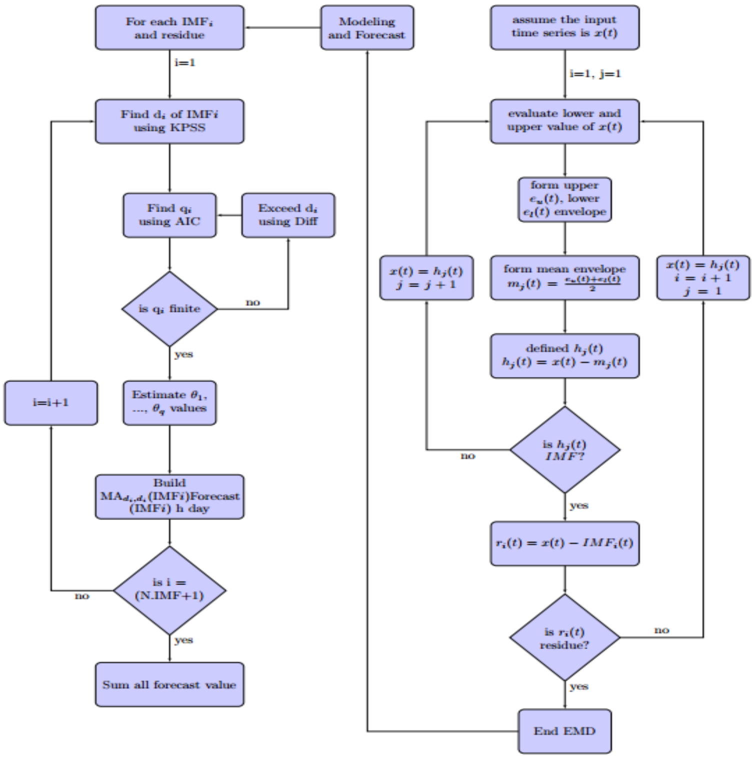

Figure 2: Flowchart of empirical mode decomposition with moving average estimation process

Table 2: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of Australia and Denmark.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
				Australia			
MAE	Holt-Winter	107.55	114.143	160.097	142.023	135.866	90.672
	MA	106.836	113.747	159.881	142.801	138.092	91.48
	ARIMA	110.362	99.267	173.24	218.579	277.756	157.907
	R.Walk	109.2	115.8	160.8	142.4	135.72	91.3
	EMD-MA	176.213	153.54	93.04	70.513	59.33	67.869
RMSE	Holt-Winter	107.55	126.292	174.81	169.45	169.046	120.56
	MA	106.836	125.823	174.664	170.114	170.929	123.37
	ARIMA	110.362	117.382	187.391	254	326.04	210.645
	R.Walk	109.2	128.027	175.568	169.857	168.888	121.898
	EMD-MA	176.213	166.799	116.893	82.858	70.487	74.805
MAPE	Holt-Winter	2.078	2.179	3.008	2.658	2.532	1.706
	MA	2.064	2.172	3.004	2.672	2.572	1.72
	ARIMA	2.131	1.899	3.247	4.016	5.004	2.902
	R.Walk	2.109	2.21	3.021	2.664	2.529	1.718
	EMD-MA	3.36	2.907	1.77	1.349	1.136	1.3
TheilU	Holt-Winter	-	1.54	2.325	2.258	2.492	1.905
	MA	-	1.534	2.324	2.266	2.519	1.953
	ARIMA	-	1.483	2.475	3.373	4.786	3.371
	R.Walk	-	1.56	2.335	2.263	2.489	1.927
	EMD-MA	-	2.003	1.616	1.008	0.887	1.017
MASE	Holt-Winter	-	1.045	1.879	1.677	1.971	1.523
	MA	-	1.042	1.877	1.687	2.003	1.537
	ARIMA	-	0.909	2.033	2.582	4.028	2.653
	R.Walk	-	1.06	1.887	1.682	1.968	1.534
	EMD-MA	-	1.406	1.092	0.833	0.86	1.14
				Denmark			
MAE	Holt-Winter	18.678	19.455	10.943	16.004	13.465	9.722
	MA	16.882	19.456	11.162	13.539	11.331	9.974
	ARIMA	15.434	29.214	21.378	25.202	14.996	9.684
	R.Walk	18.09	18.415	10.943	14.202	11.314	9.618
	EMD-MA	18.436	10.465	10.23	8.165	6.845	9.553
RMSE	Holt-Winter	18.678	21.603	11.914	19.076	17.569	11.326
	MA	16.882	21.288	11.97	16.788	15.381	11.26
	ARIMA	15.434	31.567	22.076	28.507	18.047	10.715
	R.Walk	18.09	20.516	11.661	17.328	15.44	10.921
	EMD-MA	18.436	12.487	11.333	8.374	7.648	10.437
MAPE	Holt-Winter	1.86	1.919	1.095	1.575	1.324	0.968
	MA	1.684	1.919	1.119	1.336	1.117	0.997
	ARIMA	1.591	2.851	2.18	2.454	1.474	0.967
	R.Walk	1.803	1.818	1.096	1.4	1.116	0.96
	EMD-MA	1.837	1.043	1.024	0.815	0.684	0.956
TheilU	Holt-Winter	-	1.595	0.736	1.36	1.316	0.842
	MA	-	1.553	0.682	1.185	1.152	0.808
	ARIMA	-	2.276	1.373	2.103	1.345	0.796
	R.Walk	-	1.518	0.678	1.219	1.157	0.795
	EMD-MA	-	0.955	0.692	0.523	0.573	0.727
MASE	Holt-Winter	-	1.075	0.797	1.138	0.925	0.833
	MA	-	1.076	0.813	0.963	0.778	0.855
	ARIMA	-	1.615	1.557	1.792	1.03	0.83
	R.Walk	-	1.018	0.797	1.01	0.777	0.824
	EMD-MA	-	0.578	0.745	0.58	0.47	0.819

Table 3: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of Estonia and Finland.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
				Estonia			
	Holt-Winter	11.411	7.623	5.487	7.902	6.205	4.618
	MA	11.307	7.095	5.588	6.887	5.13	3.764
MAE	ARIMA	11.381	8.557	5.954	5.239	8.054	4.663
	R.Walk	11.1	7.06	5.487	6.75	5.022	3.768
	EMD-MA	10.613	5.806	5.434	5.958	4.253	3.918
	Holt-Winter	11.411	9.541	5.778	9.444	8.304	6.623
	MA	11.307	9.091	5.653	8.439	7.109	5.406
RMSE	ARIMA	11.381	10.164	7.108	6.858	10.232	6.591
	R.Walk	11.1	8.98	5.66	8.328	7.005	5.473
	EMD-MA	10.613	7.913	7.057	7.831	6.571	6.06
	Holt-Winter	1.274	0.849	0.615	0.878	0.689	0.514
	MA	1.262	0.791	0.627	0.766	0.571	0.42
MAPE	ARIMA	1.27	0.952	0.671	0.584	0.892	0.519
	R.Walk	1.239	0.787	0.615	0.751	0.559	0.42
	EMD-MA	1.186	0.648	0.607	0.663	0.474	0.437
	Holt-Winter	-	1.204	0.765	1.388	1.291	1.123
	MA	-	1.151	0.713	1.222	1.105	0.911
TheilU	ARIMA	-	1.265	0.797	0.951	1.591	1.114
	R.Walk	-	1.136	0.733	1.207	1.088	0.923
	EMD-MA	-	1.007	1.043	1.109	1.022	1.031
	Holt-Winter	-	0.687	0.87	1.319	0.985	0.894
	MA	-	0.639	0.886	1.15	0.814	0.728
MASE	ARIMA	-	0.771	0.944	0.875	1.278	0.902
	R.Walk	-	0.636	0.87	1.127	0.797	0.729
	EMD-MA	-	0.523	0.862	0.995	0.675	0.758
				Finland			
	Holt-Winter	73.873	44.396	130.482	116.801	75.751	72.09
	MA	74.028	40.636	127.774	115.829	74.243	71.344
MAE	ARIMA	63.13	36.489	128.425	142.609	733.177	110.78
	R.Walk	73.91	44.345	128.513	113.895	74.474	70.338
	EMD-MA	83.051	50.434	102.561	86.884	70.545	46.876
	Holt-Winter	73.873	57.775	135.746	133.831	86.803	94.919
	MA	74.028	55.016	132.942	132.376	84.273	93.607
RMSE	ARIMA	63.13	39.002	133.648	160.675	870.188	136.865
	R.Walk	73.91	57.725	133.653	130.688	84.876	91.631
	EMD-MA	83.051	66.314	106.423	99.441	74.543	52.285
	Holt-Winter	2.271	1.362	3.882	3.455	2.274	2.147
	MA	2.276	1.248	3.804	3.428	2.231	2.126
MAPE	ARIMA	1.947	1.144	3.823	4.181	34.843	3.246
	R.Walk	2.272	1.36	3.826	3.373	2.237	2.097
	EMD-MA	2.546	1.542	3.079	2.6	2.134	1.419
	Holt-Winter	-	1.101	2.864	2.188	1.529	1.751
	MA	-	1.052	2.802	2.163	1.477	1.724
TheilU	ARIMA	-	0.307	2.813	2.619	15.753	2.508
	R.Walk	-	1.1	2.816	2.137	1.491	1.69
	EMD-MA	-	1.265	2.194	1.623	1.219	0.935
	Holt-Winter	-	0.601	3.21	1.944	1.532	1.466
	MA	-	0.55	3.143	1.928	1.502	1.45
MASE	ARIMA	-	0.494	3.159	2.374	14.83	2.252
	R.Walk	-	0.6	3.161	1.896	1.506	1.43
	EMD-MA	-	0.682	2.523	1.446	1.427	0.953

Table 4: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of France and India.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
			France				
	Holt-Winter	77.805	96.562	59.754	153.766	164.095	161.6
	MA	76.768	100.225	62.746	153.597	158.413	156.532
MAE	ARIMA	56.261	71.211	33.074	146.894	224.058	225.527
	R.Walk	76.89	95.605	58.677	151.027	160.902	158.305
	EMD-MA	108.038	111.826	80.201	129.286	93.759	88.662
	Holt-Winter	77.805	104.061	74.985	162.638	181.513	186.751
	MA	76.768	107.247	78.515	162.253	175.956	181.066
RMSE	ARIMA	56.261	77.041	35.562	156.364	251.215	254.839
	R.Walk	76.89	103.045	73.309	159.73	178.052	183.031
	EMD-MA	108.038	116.958	96.167	137.742	108.867	110.694
	Holt-Winter	1.736	2.128	1.321	3.314	3.506	3.434
	MA	1.713	2.207	1.385	3.31	3.389	3.331
MAPE	ARIMA	1.262	1.579	0.741	3.17	4.708	4.716
	R.Walk	1.716	2.107	1.297	3.257	3.44	3.367
	EMD-MA	2.395	2.456	1.764	2.802	2.04	1.922
	Holt-Winter	-	1.76	1.352	3.133	2.723	2.976
	MA	-	1.8	1.417	3.124	2.641	2.885
TheilU	ARIMA	-	1.309	0.353	3.017	3.775	4.053
	R.Walk	-	1.743	1.32	3.074	2.671	2.917
	EMD-MA	-	1.9	1.712	2.655	1.64	1.765
	Holt-Winter	-	1.256	0.892	3.091	2.488	2.659
	MA	-	1.303	0.936	3.088	2.402	2.575
MASE	ARIMA	-	0.926	0.493	2.953	3.397	3.71
	R.Walk	-	1.243	0.875	3.036	2.439	2.604
	EMD-MA	-	1.454	1.197	2.599	1.421	1.459
			India				
	Holt-Winter	541.111	433.938	321.473	737.767	487.473	484.4
	MA	560.392	461.068	314.904	763.766	499.961	498.051
MAE	ARIMA	437.048	367.265	198.675	1015.457	635.86	662.853
	R.Walk	554.5	451.26	343.85	752.077	507.155	502.264
	EMD-MA	440.834	555.276	469.23	670.752	402.625	452.674
	Holt-Winter	541.111	511.861	441.013	797.071	579.256	613.526
	MA	560.392	542.853	448.577	822.565	593.753	630.742
RMSE	ARIMA	437.048	455.046	213.497	1097.276	759.687	832.185
	R.Walk	554.5	529.625	463.39	812.503	602.829	636.811
	EMD-MA	440.834	616.216	586.7	731.441	479.589	576.416
	Holt-Winter	2.131	1.698	1.256	2.827	1.88	1.86
	MA	2.205	1.801	1.23	2.923	1.927	1.91
MAPE	ARIMA	1.728	1.441	0.787	3.843	2.432	2.518
	R.Walk	2.183	1.764	1.342	2.88	1.954	1.926
	EMD-MA	1.743	2.162	1.82	2.577	1.56	1.741
	HW	-	1.272	1.313	2.599	1.695	1.936
	MA	-	1.348	1.337	2.68	1.737	1.99
TheilU	ARIMA	-	1.147	0.574	3.613	2.23	2.625
	R.Walk	-	1.314	1.379	2.652	1.767	2.009
	EMD-MA	-	1.483	1.741	2.389	1.401	1.822
	Holt-Winter	-	0.783	0.883	2.869	1.541	1.702
	MA	-	0.832	0.865	2.97	1.58	1.75
MASE	ARIMA	-	0.662	0.545	3.949	2.009	2.329
	R.Walk	-	0.814	0.944	2.924	1.603	1.765
	EMD-MA	-	1.001	1.288	2.608	1.272	1.59

Table 5: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of Lithuania and Malaysia.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
				Lithuania			
	Holt-Winter	5.725	2.843	2.507	1.88	3.283	3.138
	MA	5.703	2.823	2.501	1.87	3.153	2.972
MAE	ARIMA	6.312	3.166	2.746	1.986	2.972	3.201
	R.Walk	5.62	2.81	2.507	1.88	3.164	2.967
	EMD-MA	5.058	2.628	2.393	1.817	3.295	2.595
	Holt-Winter	5.725	3.118	2.604	2.122	3.781	3.782
	MA	5.703	3.088	2.604	2.103	3.672	3.63
RMSE	ARIMA	6.312	3.882	2.885	2.261	3.513	3.838
	R.Walk	5.62	3.048	2.61	2.123	3.682	3.626
	EMD-MA	5.058	2.65	2.52	2.15	3.806	3.225
	Holt-Winter	1.171	0.583	0.516	0.387	0.68	0.65
	MA	1.166	0.579	0.515	0.385	0.653	0.616
MAPE	ARIMA	1.289	0.648	0.566	0.407	0.615	0.663
	R.Walk	1.149	0.577	0.516	0.387	0.655	0.615
	EMD-MA	1.036	0.54	0.493	0.374	0.682	0.537
	Holt-Winter	-	0.734	0.702	0.685	1.288	1.359
	MA	-	0.725	0.702	0.677	1.248	1.305
TheilU	ARIMA	-	0.963	0.754	0.646	1.191	1.379
	R.Walk	-	0.71	0.703	0.686	1.251	1.303
	EMD-MA	-	0.528	0.69	0.692	1.303	1.159
	Holt-Winter	-	0.506	0.691	0.616	1.357	1.245
	MA	-	0.502	0.69	0.613	1.303	1.179
MASE	ARIMA	-	0.563	0.758	0.651	1.228	1.27
	R.Walk	-	0.5	0.691	0.616	1.307	1.177
	EMD-MA	-	0.468	0.66	0.596	1.362	1.03
				Malaysia			
	Holt-Winter	12.595	6.383	7.365	33.658	27.561	19.803
	MA	12.649	6.452	7.301	32.333	25.885	18.95
MAE	ARIMA	13.391	6.896	7.547	32.068	26.036	18.792
	R.Walk	12.84	6.42	9.563	31.968	26.204	19.033
	EMD-MA	19.113	11.769	7.251	9	12.524	20.504
	Holt-Winter	12.595	7.182	8.915	34.246	31.188	22.116
	MA	12.649	7.336	8.404	32.951	29.485	20.986
RMSE	ARIMA	13.391	7.315	9.121	32.698	29.576	20.846
	R.Walk	12.84	7.644	11.08	32.597	29.71	21.361
	EMD-MA	19.113	12.544	7.534	12.725	13.741	22.445
	Holt-Winter	0.755	0.383	0.445	1.987	1.626	1.175
	MA	0.758	0.387	0.441	1.91	1.529	1.125
MAPE	ARIMA	0.803	0.414	0.456	1.895	1.538	1.116
	R.Walk	0.77	0.385	0.578	1.889	1.548	1.129
	EMD-MA	1.142	0.704	0.434	0.537	0.753	1.241
	Holt-Winter	-	0.753	0.932	3.099	1.633	1.251
	MA	-	0.774	0.876	2.944	1.543	1.184
TheilU	ARIMA	-	0.727	0.989	2.909	1.548	1.175
	R.Walk	-	0.823	1.129	2.901	1.555	1.21
	EMD-MA	-	1.255	0.865	0.479	0.559	1.127
	Holt-Winter	-	0.497	0.975	3.68	1.656	1.473
	MA	-	0.502	0.966	3.535	1.555	1.41
MASE	ARIMA	-	0.537	0.999	3.506	1.564	1.398
	R.Walk	-	0.5	1.266	3.495	1.574	1.416
	EMD-MA	-	0.917	0.96	0.984	0.752	1.525

Table 6: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of Netherlands and Norwegian.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
			Netherlands				
MAE	Holt-Winter	8.03	10.315	5.78	12.941	14.83	13.967
	MA	7.648	10.61	5.802	12.738	14.351	13.884
	ARIMA	5.574	12.559	4.829	11.471	18.045	26.872
	RW	8	10.24	5.727	12.765	14.582	13.662
	EMD-MA	10.11	9.374	7.373	7.732	5.342	4.622
RMSE	Holt-Winter	8.03	11.073	6.881	13.999	16.425	16.348
	MA	7.648	11.322	6.837	13.792	15.953	16.18
	ARIMA	5.574	13.299	5.74	12.442	20.288	30.986
	RW	8	10.994	6.812	13.811	16.154	16.014
	EMD-MA	10.11	9.974	8.394	8.662	6.353	5.939
MAPE	Holt-Winter	1.873	2.371	1.339	2.928	3.322	3.117
	MA	1.785	2.437	1.344	2.883	3.218	3.1
	ARIMA	1.307	2.871	1.136	2.605	4.002	5.78
	RW	1.866	2.354	1.327	2.889	3.268	3.052
	EMD-MA	2.346	2.16	1.704	1.773	1.229	1.061
TheilU	Holt-Winter	-	1.793	1.135	2.448	2.499	2.632
	MA	-	1.82	1.117	2.413	2.429	2.603
	ARIMA	-	2.117	0.553	2.168	3.096	4.984
	RW	-	1.78	1.122	2.412	2.458	2.578
	EMD-MA	-	1.597	1.345	1.489	0.965	0.953
MASE	Holt-Winter	-	1.289	0.812	2.213	2.145	2.18
	MA	-	1.326	0.815	2.179	2.075	2.167
	ARIMA	-	1.57	0.678	1.962	2.609	4.195
	RW	-	1.28	0.804	2.183	2.109	2.133
	EMD-MA	-	1.172	1.035	1.323	0.773	0.721
			Norwegian				
MAE	Holt-Winter	14.178	13.965	19.711	23.471	19.127	13.468
	MA	14.83	14.768	20.289	23.68	19.539	13.944
	ARIMA	10.697	5.051	24.578	12.095	109.898	192.283
	R.Walk	14.68	14.57	20.223	23.807	19.516	14.023
	EMD-MA	11.692	15.878	20.127	19.108	15.839	13.84
RMSE	Holt-Winter	14.178	15.684	21.631	26.199	23.719	17.192
	MA	14.83	16.539	22.268	26.455	24.138	17.779
	ARIMA	10.697	5.053	28.797	16.574	132.708	233.532
	R.Walk	14.68	16.314	22.183	26.567	24.141	17.928
	EMD-MA	11.692	18.197	22.95	21.467	19.659	17.262
MAPE	Holt-Winter	2.721	2.644	3.658	4.286	3.49	2.488
	MA	2.842	2.791	3.761	4.322	3.562	2.573
	ARIMA	2.066	0.992	5.13	2.466	16.273	116.094
	R.Walk	2.814	2.755	3.749	4.344	3.558	2.586
	EMD-MA	2.254	2.99	3.725	3.523	2.917	2.559
TheilU	Holt-Winter	-	1.438	2.201	2.668	2.513	1.975
	MA	-	1.513	2.268	2.695	2.558	2.043
	ARIMA	-	0.334	3.021	1.717	14.042	27.004
	R.Walk	-	1.493	2.257	2.706	2.558	2.063
	EMD-MA	-	1.687	2.374	2.192	2.084	1.974
MASE	Holt-Winter	-	0.951	1.799	2.172	1.863	1.621
	MA	-	1.006	1.852	2.191	1.903	1.679
	ARIMA	-	0.344	2.244	1.119	10.706	23.15
	R.Walk	-	0.993	1.846	2.203	1.901	1.688
	EMD-MA	-	1.082	1.837	1.768	1.543	1.666

Table 7: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of Slovenia and Switzerland.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
			Slovenia				
MAE	Holt-Winter	69.989	62.954	41.532	81.287	68.163	60.134
	MA	73.429	65.575	43.834	81.356	68.328	60.104
	ARIMA	60.641	73.604	26.903	58.056	69.045	116.231
	R.Walk	74.36	67.14	46.5	81.635	68.088	59.45
	EMD-MA	88.208	65.757	50.281	59.943	37.784	38.383
RMSE	Holt-Winter	69.989	72.413	58.256	91.887	84.818	80.085
	MA	73.429	75.381	61.634	92.005	84.916	79.905
	ARIMA	60.641	83.406	27.904	66.642	86.341	141.753
	R.Walk	74.36	76.747	63.918	92.261	84.738	79.364
	EMD-MA	88.208	77.681	68.076	67.297	48.04	49.778
MAPE	Holt-Winter	2.5	2.225	1.469	2.82	2.362	2.081
	MA	2.619	2.315	1.547	2.822	2.368	2.081
	ARIMA	2.173	2.59	0.968	2.035	2.391	3.92
	R.Walk	2.652	2.369	1.64	2.832	2.36	2.058
	EMD-MA	3.13	2.319	1.769	2.1	1.331	1.347
TheilU	Holt-Winter	-	1.328	1.26	2.214	2.05	2.119
	MA	-	1.382	1.333	2.217	2.052	2.114
	ARIMA	-	1.517	0.446	1.589	2.087	3.74
	R.Walk	-	1.403	1.382	2.223	2.048	2.1
	EMD-MA	-	1.44	1.471	1.597	1.16	1.313
MASE	Holt-Winter	-	0.847	0.796	2.299	1.784	1.932
	MA	-	0.882	0.84	2.301	1.788	1.931
	ARIMA	-	0.99	0.516	1.642	1.807	3.735
	R.Walk	-	0.903	0.891	2.309	1.782	1.91
	EMD-MA	-	0.884	0.964	1.696	0.989	1.233
			Switzerland				
MAE	Holt-Winter	161.271	167.702	95.689	211.783	235.662	123.634
	MA	154.555	186.691	102.415	197.672	233.418	119.939
	ARIMA	109.378	247.914	151.49	244.356	568.996	100.892
	R.Walk	163.5	169.85	98.166	212.824	235.16	126.467
	EMD-MA	186.58	114.175	85.267	165.944	76.906	100.315
RMSE	Holt-Winter	161.271	186.253	121.217	231.94	264.67	146.838
	MA	154.555	203.947	127.003	219.645	260.841	143.845
	ARIMA	109.378	264.537	185.511	276.961	636.225	123.678
	R.Walk	163.5	188.499	124.478	233.049	264.124	149.913
	EMD-MA	186.58	137.627	108.249	169.317	92.817	115.299
MAPE	Holt-Winter	1.873	1.928	1.106	2.402	2.653	1.415
	MA	1.796	2.141	1.183	2.245	2.629	1.375
	ARIMA	1.278	2.823	1.735	2.755	6.12	1.162
	R.Walk	1.898	1.952	1.134	2.413	2.647	1.447
	EMD-MA	2.16	1.321	0.987	1.893	0.882	1.162
TheilU	Holt-Winter	-	1.521	1.104	2.275	2.361	1.283
	MA	-	1.644	1.143	2.168	2.322	1.236
	ARIMA	-	2.081	1.713	2.8	5.669	0.997
	R.Walk	-	1.539	1.137	2.286	2.356	1.317
	EMD-MA	-	1.168	0.997	1.441	0.793	0.795
MASE	Holt-Winter	-	1.026	0.761	2.141	2.055	1.181
	MA	-	1.142	0.814	1.998	2.036	1.146
	ARIMA	-	1.516	1.204	2.47	4.963	0.964
	R.Walk	-	1.039	0.78	2.151	2.051	1.208
	EMD-MA	-	0.698	0.678	1.677	0.671	0.958

Table 8: Presented the RMSE, MAE, MASE, MAPE and TheilU of proposed method and four forecasting methods for forecasting at h = 1, 2, 3, 4, 5 and 6 for stock market data of Thailand and UK.

Countries	Method	h=1	h=2	h=3	h=4	h=5	h=6
			Thailand				
MAE	Holt-Winter	34.516	17.239	15.972	36.169	26.028	22.715
	MA	35.23	17.456	15.773	37.428	27.04	23.973
	ARIMA	35.522	17.605	18.143	37.805	27.49	24.438
	R.Walk	35.21	17.605	17.34	37.615	27.548	24.35
	EMD-MA	26.583	16.985	26.014	35.632	12.299	10.186
RMSE	Holt-Winter	34.516	19.832	21.805	39.039	31.022	29.433
	MA	35.23	20.159	21.835	40.347	32.237	31.03
	ARIMA	35.522	20.503	23.874	40.747	32.781	31.629
	R.Walk	35.21	20.709	23.103	40.572	32.858	31.53
	EMD-MA	26.583	21.92	30.12	38.399	16.065	13.672
MAPE	Holt-Winter	2.741	1.377	1.266	2.812	2.031	1.77
	MA	2.796	1.394	1.25	2.906	2.107	1.865
	ARIMA	2.818	1.405	1.435	2.935	2.141	1.9
	R.Walk	2.794	1.405	1.372	2.92	2.146	1.894
	EMD-MA	2.124	1.353	2.045	2.771	0.973	0.806
TheilU	Holt-Winter	-	0.768	1.02	1.996	1.558	1.616
	MA	-	0.782	1.026	2.064	1.62	1.703
	ARIMA	-	0.798	1.116	2.086	1.648	1.736
	R.Walk	-	0.81	1.08	2.077	1.652	1.731
	EMD-MA	-	0.876	1.387	1.951	0.796	0.743
MASE	Holt-Winter	-	0.49	0.762	2.087	1.359	1.405
	MA	-	0.496	0.753	2.16	1.412	1.483
	ARIMA	-	0.5	0.866	2.182	1.436	1.512
	R.Walk	-	0.5	0.827	2.171	1.439	1.506
	EMD-MA	-	0.482	1.241	2.056	0.642	0.63
			UK				
MAE	Holt-Winter	116.446	119.834	64.053	173.492	169.506	181.177
	MA	116.798	128.207	70.107	179.265	172.259	184.647
	ARIMA	71.493	99.864	121.873	201.234	170.644	251.493
	R.Walk	119.3	123.45	67.7	177.775	174.02	185.517
	EMD-MA	163.535	127.739	109.383	150.234	114.16	80.502
RMSE	Holt-Winter	116.446	133.327	80.751	185.725	192.645	209.494
	MA	116.798	141.107	87.079	191.694	196.168	213.262
	ARIMA	71.493	109.732	122.871	214.97	197.451	277.314
	R.Walk	119.3	137.106	85.094	190.265	197.528	214.245
	EMD-MA	163.535	147.403	132.608	157.971	127.377	90.184
MAPE	Holt-Winter	1.918	1.954	1.052	2.781	2.704	2.872
	MA	1.924	2.088	1.15	2.871	2.746	2.925
	ARIMA	1.186	1.635	2.052	3.21	2.72	3.939
	R.Walk	1.964	2.012	1.111	2.848	2.774	2.938
	EMD-MA	2.673	2.077	1.78	2.42	1.841	1.298
TheilU	Holt-Winter	-	1.494	0.977	2.398	2.104	2.475
	MA	-	1.569	1.064	2.481	2.144	2.519
	ARIMA	-	1.218	1.258	2.809	2.16	3.261
	R.Walk	-	1.535	1.042	2.462	2.158	2.531
	EMD-MA	-	1.687	1.639	1.966	1.384	0.985
MASE	Holt-Winter	-	1.004	0.7	2.294	1.804	2.222
	MA	-	1.075	0.766	2.37	1.834	2.265
	ARIMA	-	0.837	1.331	2.661	1.816	3.085
	R.Walk	-	1.035	0.739	2.35	1.852	2.276
	EMD-MA	-	1.071	1.195	1.986	1.215	0.988

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