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A Hybrid Model of MEMD and PSO-LSSVR for Steel Price Forecasting

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ABTRACT

Herein, we propose a novel hybrid method for forecasting steel prices by modeling nonlinearity and time variations together to enhance forecasting adaptability. The multivariate empirical mode decomposition (MEMD)–ensemble-EMD (EEMD) approach was employed for preprocessing to separate the nonlinear and time variation components of a hot-rolled coil (HRC) price return series, and a particle swarm optimization (PSO)-based least squares support vector regression (LSSVR) approach and a generalized autoregressive conditional heteroskedasticity (GARCH) model were applied to capture the nonlinear and time variation characteristics of steel returns, respectively. The empirical results revealed that compared with the traditional models, the proposed hybrid method yields superior forecasting performance for HRC returns. The evidence also suggested that in capturing the price dynamics of HRC during the COVID-19 pandemic period, the asymmetric GARCH model with MEMD–LSSVR outperformed not only standard GARCH models but also the EEMD-LSSVR models. The proposed MEMD–LSSVR–GARCH model for steel price forecasting provides a useful decision support tool for steelmakers and consumers to evaluate steel price trends.

Keywords-- Steel, Forecast, MEMD, EEMD, LSSVR

I. INTRODUCTION

Steel is a material central to modern society, and the steel industry is considered a key infrastructure industry. Despite the continual development of new construction materials, steel remains widely used in numerous sectors, such as the construction, mechanical equipment, automotive, and other transportation sectors. Further, steel is and will continue to be crucial to the global energy supply, whether that energy generation is based on fossil fuels, nuclear technology, or renewable sources such as wind power. Historically, early and precise prediction of steel prices has been a critical issue for producers, traders, and steel product end-users. During the coronavirus-related shutdowns of early 2020, many steel mills halted production due to the fear of a deep recession. However, the demand for steel-based products such as grills and refrigerators quickly reemerged. Consequently, the benchmark price for hot-rolled steel increased to a high of US$1800/ton as global economies reopened in 2021. Prior to the pandemic, hot-rolled steel traded in the range of $500 to $800 per ton. After an initial price drop at the outset of the pandemic, steel prices increased rapidly from August 2020 as the rising demand far outweighed supply. The unprecedented price drop and rise in demand that have occurred over the past few years have caused steel price volatility, thereby making the accurate prediction of steel prices difficult. However, the early estimation of prices is critical in the steel industry.

As with any commodity, supply and demand are the principal factors that determine steel prices. However, the price of steel is also determined by forecasted supply and demand, which can be more accurately predicted when more information is available. Since 2008, steel products, including hot-rolled coil (HRC), futures contracts have been traded on commodity exchange markets, including the Chicago Mercantile Exchange, Shanghai Futures Exchange, and London Metal Exchange. This suggests that steel has been financialized—although it remains a physical asset as well; nevertheless, forecasting financial assets is a challenging task. As indicated by Garcia, Irwin, and Smith (2015), future prices are difficult to predict because market imperfections are quickly discovered, exploited, and corrected by market traders and participants. Nonetheless, forecasting a financial time series such as that for the price of steel is a highly active research area, with applications spanning from hedging strategies to risk management to protecting against economic fluctuations. Although various studies on the steel industry (Ou, Cheng, Chen, and Perng, 2016; Mehmanpazir, Khalili-Damghani, and Hafezalkotob, 2019; Ma, 2021) have been undertaken, comprehensive investigations of steel prices are still lacking.

Steel price movement in the commodity market is affected by a combination of economic and industrial trends, raw material and shipping costs, and economic

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noise—these constitute the distinct features that emerge over various time horizons. Traditionally, determinant variables have been employed for the linear prediction of steel prices (Mancke, 1968; Kapl and Muller, 2010; Malanichev and Vorob'ev, 2011). However, some studies have characterized steel price returns on the basis of nonlinear behavior by using either econometric models or artificial neural networks and fuzzy approaches (Chou, 2012; Kahraman and Unal, 2012; Chen, Li, and Yu, 2021). Therefore, steel price movement can be analyzed using technical tools (e.g., machine learning algorithms), econometric models, or a combination of these methods. Few studies, however, have combined econometric models and machine learning approaches to predict steel prices. In the present study, given the nonlinear and changeable characteristics of steel prices, a novel hybrid method of forecasting steel prices by modeling nonlinearity and time variations simultaneously is proposed. By combining two models, adaptability was enhanced, and distinct aspects of the underlying patterns of steel price return movement could be well captured.

In this study, the proposed method for steel price forecasting is a hybrid of the multivariate empirical mode decomposition (MEMD), least squares support vector regression (LSSVR), and generalized autoregressive conditional heteroskedasticity (GARCH), models; the hybrid is based on the advantages of econometric models and machine learning algorithms for depicting the nonlinear, dynamic features of steel price returns. The MEMD model is widely employed to decompose steel price returns into a series of intrinsic mode functions (IMFs) and residuals, and the LSSVR method is used to forecast nonlinear components. The GARCH model (including asymmetric GARCH) is used to capture the time variation component more accurately. In the end, the sum of the forecasted values for all components yields the final forecasted results of steel price returns.

II. RELATED FORECASTING LITERATURE

The price fluctuations of a commodity such as steel are of interest because they affect the decision-making of producers and consumers; hence, developing accurate price forecasts is crucial. Econometric specification models (Beck, 2001) provide valuable insights into the determinants of commodity price movements, but such models are not necessarily the best choice for forecasting purposes. Studies have demonstrated that the accuracy of forecasting commodity price volatility by using machine learning algorithms can be more precise than the accuracy of forecasting such volatility by using standard GARCH-type models (e.g., Fałdzinski *et al.*, 2021). However, in several other studies, asymmetric GARCH–based models exhibited the most accurate forecasting. Therefore, the results of empirical studies have been mixed. A hybrid modeling approach that integrates machine learning with econometric models is likely to outperform the models proposed in previous studies.

2.1 Application of MEMD Algorithm in Forecasting

Wu and Huang (2009) extended the EMD algorithm and proposed the ensemble EMD (EEMD) algorithm, which can be used to analyze sequences effectively and reduce the influence of mode mixing for the EMD algorithm. The EEMD algorithm is employed to decompose an original time series into several IMFs and a residual sequence. It is widely used in complex system analysis, and those results further validate the effectiveness of the EEMD method (Tang *et al.*, 2015; Yu *et al.*, 2016). MEMD is a new multiscale data-adaptive decomposition and analysis model for multivariate data. It extends the classic oscillation concept in the univariate EMD model to use multivariate joint oscillation and adopts a generalized rotational mode (Mandic *et al.*, 2013; Park *et al.*, 2013).

Although the empirical results of EEMD and MEMD are favorable when compared with other energy and metal price forecasting methods, such as those for the forecasting of wind, port container throughput, and air travel demand (Wang *et al.*, 2011; Hu *et al.*, 2013; Xie *et al.*, 2013; Yu *et al.*, 2014; Zhang *et al.*, 2015; He *et al.*, 2017), studies investigating applications of the MEMD algorithm in steel price forecasting remain scarce.

2.2 Application of LSSVR Algorithm in Forecasting

The LSSVR method, an improved version of SVR, has received considerable recent attention among prediction methods due to its fast computational speedand the LSSVR method's use of the linear squares principle for the loss function instead of the quadratic programming employed in the SVR method.

LSSVR has been widely used in oil price forecasting, port container throughput forecasting, air travel demand forecasting, and hydropower generation (Wang *et al.*, 2011; Xie *et al.*, 2013; Yu *et al.*, 2014). To forecast foreign exchange rates, Lin *et al.* (2012) proposed the EMD–LSSVR model, which outperformed the EMD-based autoregressive integrated moving average (EMD–ARIMA), LSSVR, and ARIMA models. Moreover, Zhang *et al.* (2008) used EEMD to analyze fundamental features of petroleum price series over different time horizons and indicated that the decomposed terms can be introduced into the SVR to predict prices more precisely.

2.3 Application of GARCH Model in Forecasting

GARCH models, initially proposed by Bollerslev (1986) and Taylor (1986), have been applied successfully in modeling the volatility of variables in time series, with applications occurring primarily in the area of financial investments. After identifying an asymmetric relationship between conditional volatility and conditional mean value,

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econometrists have focused on the design of models to explain this phenomenon. Thus, asymmetric GARCH models are employed to capture the asymmetric characteristics of volatility. The empirical evidence of Nelson (1991) and Glosten *et al.* 1989, 1993) indicates that asymmetric models outperform standard GARCH models in terms of forecasting volatility over shorter time horizons.

III. FORECASTING METHODOLOGIES AND DATA

3.1 EEMD and MEMD Algorithms

MEMD, a popular method that is the extension of the EMD and EEMD algorithms, as demonstrated by its applications in many fields, such as texture analysis, finance, image processing, ocean engineering, and seismic research. EMD, first proposed by Huang *et al.* (1998), is a novel empirical analysis tool used for processing nonlinear and nonstationary datasets. The main idea of EMD is to decompose a nonlinear and nonstationary time series into a sum of several simple IMF components and one residue with individual intrinsic time-scale properties.

Let (t) be a given original steel return time series; the detailed steps of the EMD calculation can then be described as follows.

Step 1. Find all the local extremes of the original steel return series (t).

Step 2. Calculate the upper envelope $S_{up}(t)$, which can be derived by connecting all the local maxima by using cubic spline interpolation. Similarly, the lower envelope $S_{low}(t)$ can be obtained, and the average envelope $A(t)$ can be calculated based on the upper and lower envelopes as follows:

$$A(t) = \frac{[S_{up}(t) + S_{low}(t)]}{2}$$

Step 3. Calculate the first difference $S_1(t)$ to obtain the oscillatory mode between the original series value $S(t)$ and the mean envelope $A(t)$ as follows:

$$S_1(t) = S(t) - A(t)$$

Step 4. Check whether $S_1(t)$ satisfies the two IMF requirements. If $S_1(t)$ is an IMF, then $S_1(t)$ is denoted as the first IMF $Q_1(t)$ and $S(t)$ is replaced with the residue $C_1(t)$ as follows:

$$C_1(t) = S(t) - Q_1(t)$$

Otherwise, if $S_1(t)$ is not an IMF, replace $S(t)$ with $C_1(t)$ and repeat steps 2 and 3 until the termination criterion is satisfied. After the EMD calculation, the original time series value (t) (input signal) can be decomposed and all the IMF components and a residue can be totaled. The given equation is as follows:

$$S(t) = \sum_{i=1}^{n} Q_i(t) + C_n(t)$$

where $Q_i(t)$ $(i = 1, 2, . . . , n)$ is the IMF for a distinct decomposition and $C_n(t)$ is the residue after nIMFs are derived. This ensures each IMF is independent and specifically expresses the local characteristics of the original time series data.

The EEMD method was developed by Wu and Huang (2009) to overcome the key drawback of EMD—the mixing mode problem. EEMD involves an additional step of adding white noise, which can improve scaling and extract the actual signals (real IMFs) from data. EEMD is a completely localized and adaptive algorithm for stationary and nonstationary data (Zhang *et al.*, 2009). Therefore, EEMD differs from EMD, which is based on the hypothesis that observations are composed of real sequences and white noise.

For multivariate signals, however, the local maxima and minima cannot be defined directly, and the notion of an oscillatory mode defining a multivariate IMF is also complex (Rilling *et al.*, 2007). This makes the MEMD model especially notable in the economics and finance fields. Similar to EMD, the output of MEMD ensures the enhanced identification of intrinsic oscillatory modes within a signal. Given a *p*-variate signal s(t),MEMD produces *M* multivariate IMFs as follows:

$$S(t) = \sum_{m=1}^{M} C_m(t) + r(t)$$

where $c_m(t)$ is the mth IMF of $S(t)$ (also p variate) and $r(t)$is the *p*-variate residual.

To address this problem, multiple *p*-dimensional envelopes are generated by taking signal projections along with various directions in *p*-dimensional space and subsequently interpolating their extrema (Rehman and Mandic, 2009). These envelopes are then averaged to obtain the local multivariate mean.

3.2. LSSVR Algorithm

LSSVR is adapted from SVR but has a more efficient calculation procedure. LSSVR is a type of SVM algorithm that is based on the regularization theory proposed by Suykens *et al.* (1999, 2002). This algorithm takes the least-squares linear system as the loss function and transforms classic quadratic programming optimization problems to solve linear equations; this involves markedly less computational complexity, greater calculation efficiency, faster processing, and lower learning difficulty.

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The fundamental idea of LSSVR is to map the training set (y, x) into the high-dimensional feature space by using a nonlinear mapping function φ (·). Thereafter, linear regression is performed in the high-dimensional feature space. Additionally, LSSVR adopts equality constraints and a linear Karush–Kuhn–Tucker (KKT) system, which delivers more computational power to solve nonlinear problems.

LSSVR can thus be formulated as follows:

$$y(x) = \omega^T\varphi(x) + q$$

where $\varphi(x)$ is the nonlinear mapping function, ω is a coefficient, and q is a deviation. Applying the principle of structural risk minimization can transform the regression problem into the following optimization problem:

$$\min\ (1/2)\ \omega^T\omega + (1/2)\ \gamma\sum e_t^2$$
$$\text{s.t. } y_t = \omega\ (x_t) + q + e_t$$

where γ is the penalty parameter and e_t is the slack variable.

Introducing the Lagrangian function and KKT conditions allows the original problem to be represented in the following form:

$$\text{y(x)} = \sum\omega_t K(x, x_t) + q$$

where $K(\cdot)$ is the kernel function.

3.3 Particle Swarm Optimization–Based LSSVR Method

The modeling performance of LSSVR relies heavily on the model parameters. Therefore, the particle swarm optimization (PSO) algorithm, a key searching algorithm that involves collaborative searching of particle swarms, was employed in this research to obtain the optimal parameters. The PSO algorithm is an evolutional technique that is based on simulations of the flocking and swarming behaviors of birds and insects (Eberhart and Kennedy, 1995); it can efficiently identify optimal or near-optimal solutions for a given problem. The PSO algorithm can select the parameters for LSSVR automatically without trial and error, thus ensuring the accuracy of parameter optimization. It is superior to other intelligent algorithms (e.g., genetic algorithms) in that it achieves faster convergence and requires fewer parameters to be set.

We define each particle as a potential solution to a problem in a d-dimensional search space; $u_i$is the current position of the particle, $v_i$is the current velocity, $p_i$is the previous position, and $p_g$is the optimal position among all the particles. The term w is the initial inertia weight, r_1 and r_2 are random numbers obeying a uniform distribution, and c_1 and c_2 are the dynamic nonlinear individual learning factor and the dynamic nonlinear population learning factor, respectively, in the tth iteration.

The optimal position of particle i can then be computed using the following equations:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i\text{-}u_i^t) + c_2r_2(p_g\text{-}u_i^t)$$

$$u_i^{t+1} = u_i^t + v_i^{t+1}$$

After acquiring the optimal model parameters in the learning process, the PSO–LSSVR model was constructed. In this research, the steps involved in the prediction algorithm PSO–LSSVR are as follows:

Step 1. Determine the ranges of penalty coefficient C and the kernel parameter of the LSSVR model.

Step 2. Initialize the PSO algorithm parameters by randomly initializing a particle to form a group of particles and randomly generating the initial velocity of the particles.

Step 3. Use the LSSVR procedures to train the initialized particles, obtain individual model fit values, and update the global and individual particle optimal values.

Step 4. Determine the termination condition. If the maximum number of iterations is reached, then stop; otherwise, produce a new group and repeat step 3 until the termination requirements are met. At this point, the individual particle in the group that has the lowest model fit value represents the optimal solution.

Step 5. Use the optimal parameter penalty factor C and kernel parameter in the LSSVR procedures, and use a test sample to obtain predictions.

3.4. Data and the Hybrid Approach

In our study, we investigated the futures contracts of a selected steel commodity, namely HRC, which is a type of sheet product resembling a wound steel strip. The product is widely used in the construction, car manufacturing, and machine industries and is a key input in industrialization. HRC is generally the most frequently produced among the products of the world's largest steelmakers. Moreover, China is the world's largest producer, consumer, and exporter of HRCs, with an annual output of hundreds of millions of tons. Thus, the primary information sources regarding steel price trends are usually the large HRC markets such as the key HRC markets of China. In this study, Chinese HRC futures contracts were quoted at the Shanghai Futures Exchange, and the trading dataset was obtained from the Datastream database. The hybrid method proposed in this research was applied to the aforementioned HRC futures price returns. We analyzed data for the 8-year period from January 2014 through October 2021. Applying the hybrid method that is able to model both nonlinearity and time variations was an appropriate approach for HRC price forecasting. Initially, the daily observations from January 2014 through October 2019 were used as the training samples, and those from November 2019 through October 2021 were considered the testing samples. From these, we determined the weekly HRC returns. We then used EEMD and MEMD to decompose the weekly HRC price return series into independent IMFs and one residual, which were defined as subseries (see Forecasting Results section).Once PSO–

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LSSVR was tuned, the same network was used to make predictions in the testing sample set. Training and validation sets were rolled forward at the end of each week, and the model was refitted.

The steps of the proposed hybrid approach are summarized as follows.

1. Decomposition: The original HRC steel price return series is first decomposed into finite IMFs and one residual series by using EEMD and MEMD. The original steel price return series can then be represented as follows:

$$S(t) = \sum_{i=1}^{n} I_i(t) + R_n(t)$$

where $S(t)$is the original steel price return series and $I_i(t)$and $R_n(t)$ represent the IMFs and residual series, respectively.

2. Observe the IMFs $I_i(t)$and residual series $R_n(t)$. Thereafter, incorporate the nonlinear and time variation components extracted from the original steel return series. If the IMF exhibits the feature of time variation, then we may define it as $I_j(t)$; otherwise, define it as $N_i(t)$. Thus, the original steel return series can be defined as follows:

$$S(t) = \sum_{i=1}^{m} N_i(t) + \sum_{j=m+1}^{n} I_j(t) + R_n(t)$$

where $N_i(t)$ and $I_j(t)$ denote the nonlinear and time variation components extracted from the original steel return series, respectively.

3. The PSO–LSSVR model is developed to forecast the future values of the nonlinear component and the residual series. The GARCH and other alternative models (asymmetric GARCH) are used to forecast the future values of the time variation component.
4. The final forecasted steel price return series is obtained by combining the forecasted results of $N_i(t)$, $I_j(t)$,and $R_n(t)$.

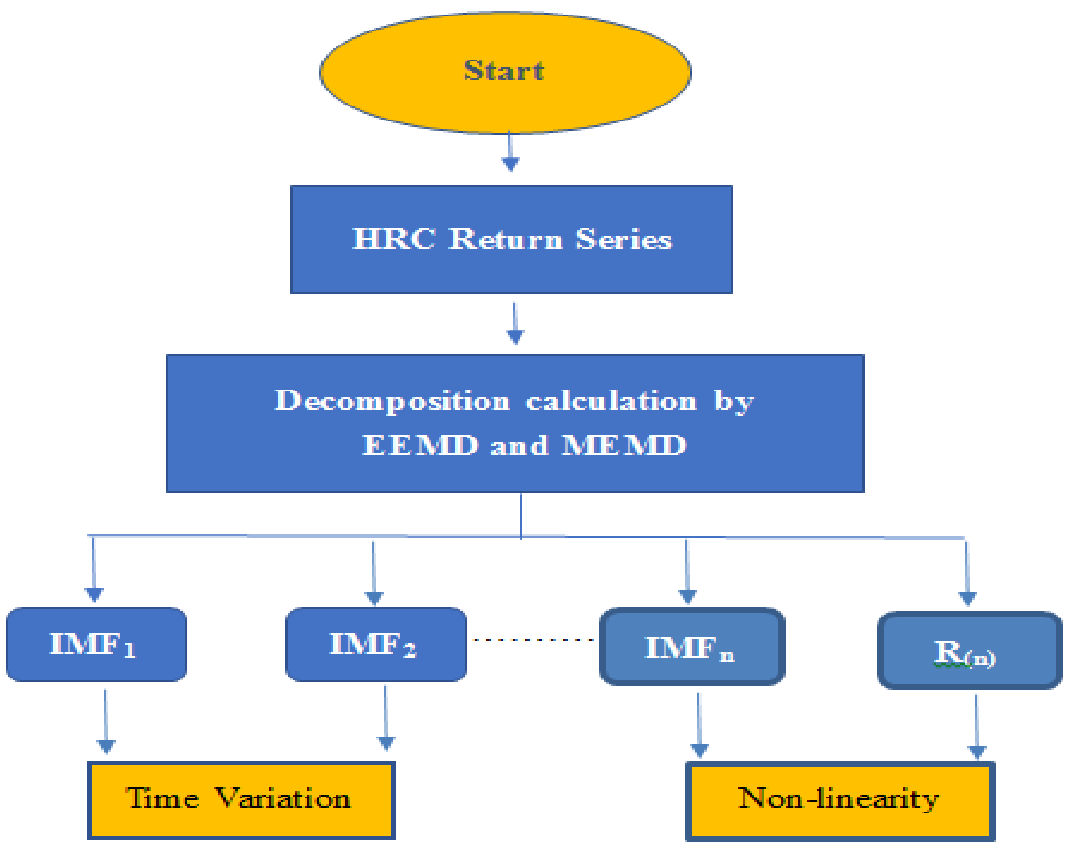

Figure 1: The procedures of steel price forecasting using the hybrid model

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IV. FORECASTING RESULTS

The descriptive statistics for HRC weekly returns are presented in Table 1. The calculated means of the returns were negative despite the prices of HRC increasing over the analyzed period. The absolute values of the minimum and maximum returns were relatively high. Additionally, a high standard deviation (2%) relative to a markedly lower mean return indicated that the observations were spread over a wider range of values, exhibiting relatively high volatility. Because the skewness of the HRC returns was between 0.5 and 1 (positively skewed), the data were moderately skewed. However, the kurtosis was greater than 3, which demonstrated that the dataset had heavier tails. Therefore, the HRC returns for our sample exhibit low skewness and high kurtosis.

Table 1: Summary Statistics of Hot Rolled Coil Weekly Returns

Commodity	Mean	Min	Max	Md	SD	Var	Skew	Kurt
Hot-Rolled Coil	**-0.06%**	**-7%**	**8.96%**	**0.12%**	**2%**	**0.04%**	**0.778**	**3.764**

Note: Mean is the arithmetic mean, Min is minimum, Max is maximum, Md is median, SD is standard deviation, Var is variance, Skewis skewness, Kurt is excess kurtosis. The sample period is January 2014 to October 2021.

Figure 2 depicts the decomposition results of the HRC return series obtained using EEMD; the time variation behavior of the training dataset was observed in IMF1, IMF2, and IMF3, which were the high-frequency components of the price series. Various alternative GARCH models were then used to forecast each of these subseries. The PSO–LSSVR model was applied for forecasting for the other subseries. We used a rolling window and applied the following procedure to estimate both the GARCH and PSO–LSSVR models. For the initial training sample (i.e., January 2014 through October 2019), we developed models and obtained forecasts for 1 week in advance. We consecutively added one new observation to the estimation sample while simultaneously removing the oldest observation. Then, on the basis of each estimation sample, we redeveloped the models and made forecasts. We repeated this procedure until we obtained forecasts for the 2-year period from November 2019 through October 2021. The GARCH models considered were GARCH, GJR-GARCH, IGARCH, APGARCH, and C-GARCH. The parameters of these models were estimated using the quasi-maximum likelihood method.

The forecasts were evaluated based on two primary measures: the mean absolute error (MAE) and root mean squared error (RMSE). The MAE is among the simplest loss functions used in forecasting studies; it measures the average magnitude of the errors in a set of forecasts without considering their direction. By contrast, the RMSE is a common means of measuring the quality of a model's fit. MAE is calculated by taking the absolute difference between the predicted and actual values and averaging it across the dataset. RMSE is the square root of the average squared difference between the predicted and actual values. MAE and RMSE are expressed as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)2}$$

where y_i is actual value, $\hat{y}_i$ is predicted value, n is sample size.

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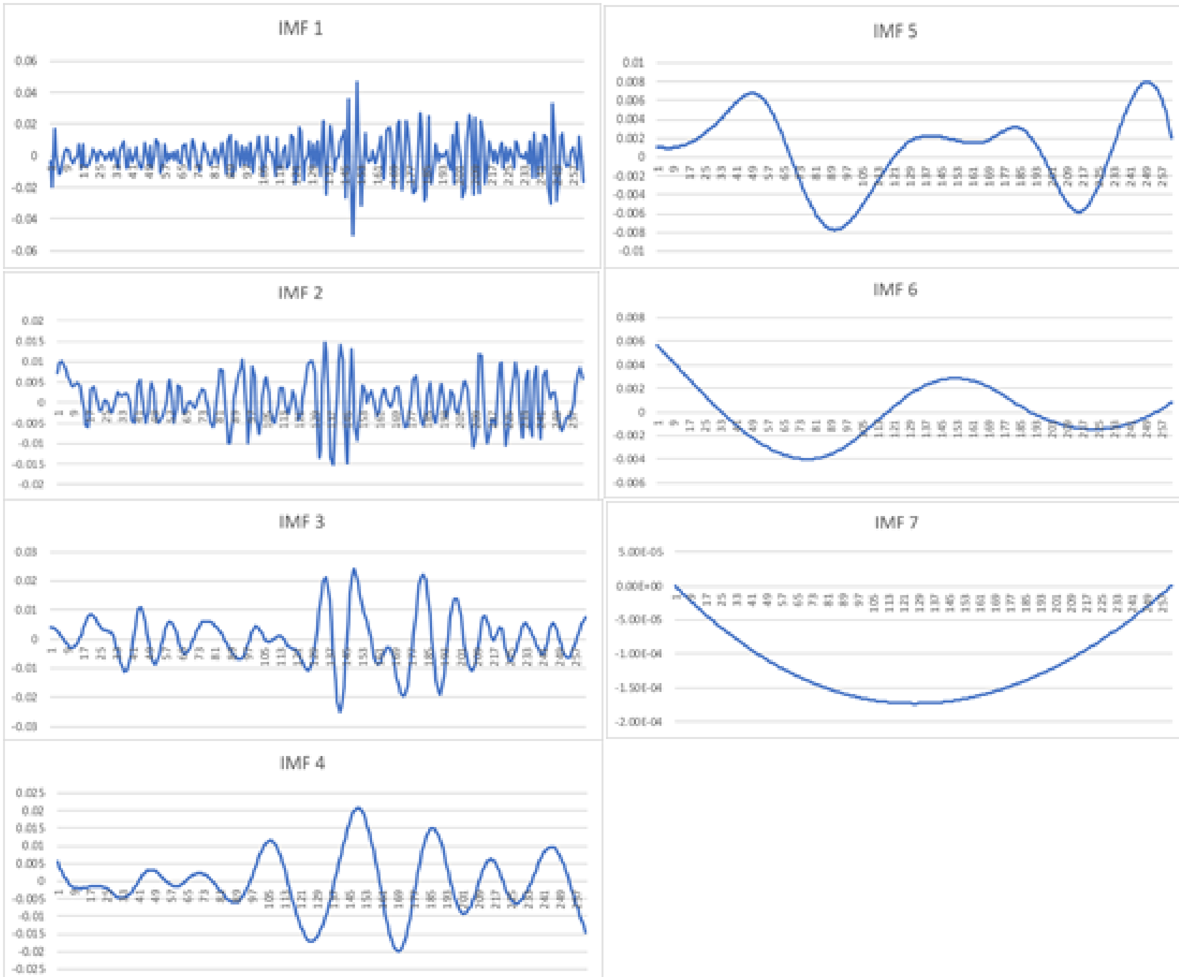

Figure 2: The decomposition results of HR Creturn series by the EEMD method

Table 2 presents the EEMD forecasting performance with the proposed hybrid approach (EEMD plus GARCH with LSSVR) when applied to the testing sample. Notably, the forecasting accuracy of Model 7 was superior to that of the other six models due to its lower MAE and RMSE values. This suggests that the CGARCH model, an asymmetric model, not only outperformed the other GARCH models but could also effectively capture the time variation volatility of HRC prices during the testing sample period.

Table 2: Evaluation of the HRC Forecasts by the EEMD Method

Model	**EEMD (Decomposition Calculation)**						
	GARCH (1)	PSO-LSSVR (2)	GARCH + PSO-LSSVM (3)	IGARCH + PSO-LSSVM (4)	GJR-GARCH + PSO-LSSVM (5)	APGARCH + PSO-LSSVM (6)	CGARCH + PSO-LSSVM (7)
MAE	3.2058%	3.4561%	2.6111%	2.6100%	2.6231%	2.9759%	2.6063%
RMSE	3.9862%	4.2127%	3.3753%	3.3734%	3.3938%	4.0177%	3.3711%

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We then developed the dataset for the empirical study of MEMD. To evaluate the performance of the proposed MEMD model against the benchmark models of EEMD (Table 2), we selected the market price data of the major raw materials of HRC, iron ore, and cooking coal. These market price variables are widely recognized as the determinants of HRC manufacturing costs and thus can be treated as supply-based forecasting factors. The data source for thesevariables was the DataStream database. As in Figure 3, the decomposed IMFs obtained using MEMD varied across more scales, exhibiting distinct behavioral and statistical characteristics that were even more obvious than those in the EEMD results presented in Figure 2. We then used the various GARCH models to forecast the high-frequency IMFs, from IMF1 to IMF4, and the PSO–LSSVR model was employed to forecast the other nonlinear IMFs. As detailed in Table 3, the forecast errors of the asymmetric GARCH model (Model 6) were not only lower than those of the other models listed in Table 3 but were also noticeably lower than those of all the models listed in Table 2.

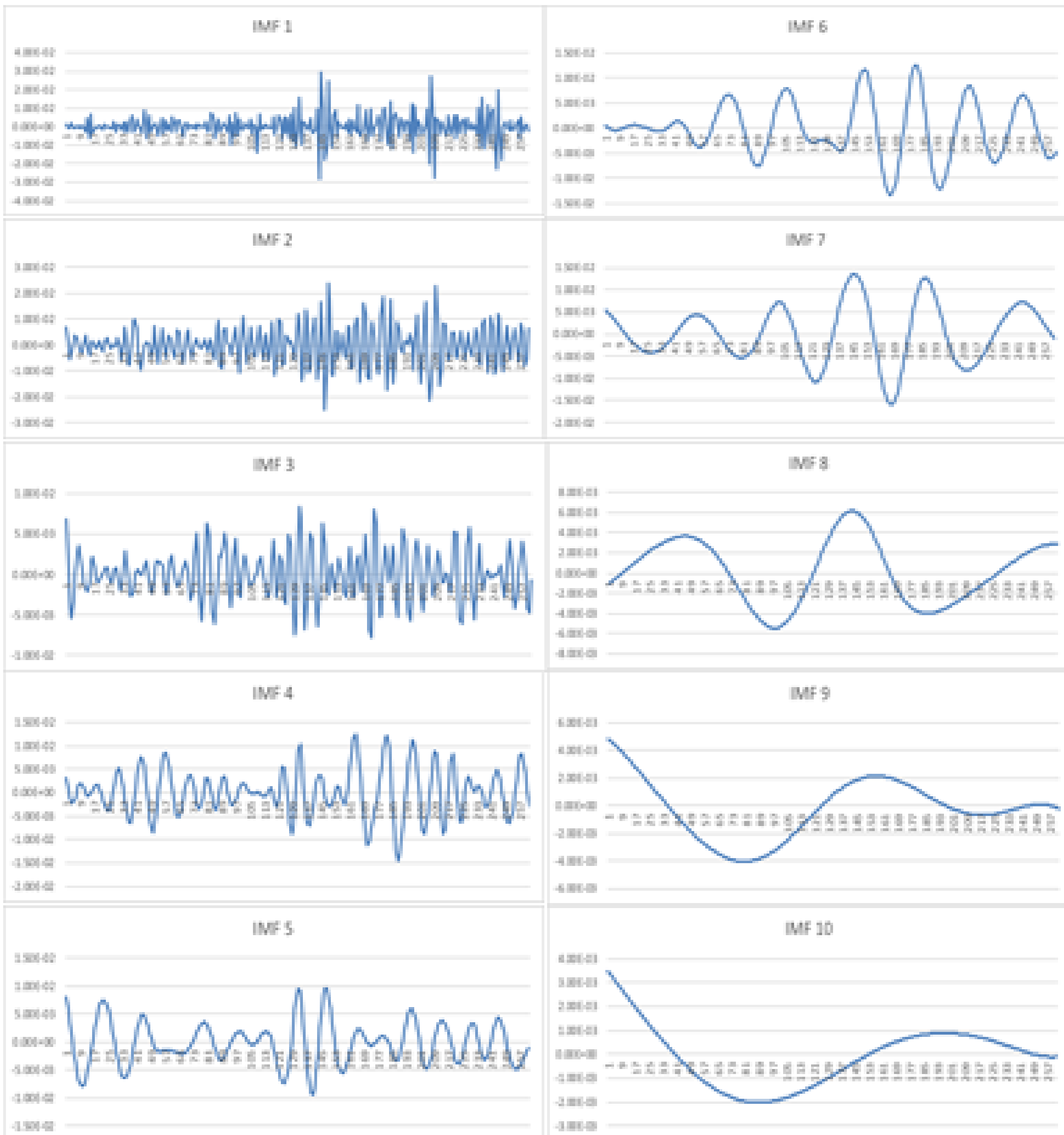

Figure 3: The decomposition results of HR Creturn series by the MEMD method

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Table 3: Evaluation of the HRC Forecasts by the MEMD Method

Model	MEMD (Decomposition Calculation)						
	GARCH (1)	PSO-LSSVR (2)	GARCH + PSO-LSSVM (3)	IGARCH + PSO-LSSVM (4)	GJR-GARCH + PSO-LSSVM (5)	APGARCH + PSO-LSSVM (6)	CGARCH + PSO-LSSVM (7)
MAE	2.1965%	2.5594%	1.8730%	1.8729%	1.8733%	1.8515%	1.9305%
RMSE	2.7354%	3.1880%	2.4230%	2.4243%	2.4236%	2.3991%	2.5358%

V. CONCLUSION

For application in the context involving the complexity of steel price movement and the uncertainty of forecasting during the COVID-19 pandemic period, we proposed a new hybrid method for HRC forecasting that considers both the nonlinearity and time variation dynamics of steel price movement by using an extension of EMD. This method is noteworthy for several reasons. First, the MEMD–EEMD approach for preprocessing was employed in this study to separate the nonlinear and time variation components of the HRC price return series, which was beneficial to model the distinct components of steel prices and yielded excellent forecasting accuracy. Second, the PSO–LSSVR approach is a popular machine learning technique capable of effectively capturing the nonlinear characteristics of steel return movement, and GARCH models are standard tools applied to capture the time variation characteristics of steel returns.

The empirical results demonstrate that compared with traditional models, the proposed hybrid method yields superior forecasting performance for HRC returns. The evidence also suggests that the asymmetric GARCH model with MEMD–LSSVR outperformed not only the standard GARCH models but also the EEMD–LSSVR models in capturing the nonlinear and time variation components of HRC prices during the testing sample period. Hence, the proposed MEMD–LSSVR–GARCH model for steel price forecasting provides a useful decision support tool for steelmakers and consumers to evaluate steel price trends and effectively measure extreme risk evolution dynamics such as the risk of COVID-19.

This study used the hybrid method to forecast steel prices on the basis of historical data. However, prices are ultimately determined not only by the quantitative results from the hybrid method but also by some sudden and unexpected events that are difficult to quantify. For example, the unilaterally imposed new tariffs on steel products suddenly announced by the US during 2018 substantially affected global steel prices. We may further consider the alternative approach by simultaneously incorporating qualitative factors and combining the quantitative and qualitative results to further enhance the approach's forecasting accuracy.

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