A New Hybrid Model Using Deep Learning to Forecast Gold Price

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Abstract–Today, different markets and economic sectors are directly or indirectly affected by gold price; thus its prediction is a big challenge for both investors and researchers. On the other hand, the nonstationary and nonlinear patterns of gold price data cause the prediction process even more complex. To address this challenge, a hybrid model was developed in this paper to predict gold price, with a concentration on enhancing accuracy through considering the gold price data characteristics. To do this, Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) and Gated recurrent units (GRU) were used to deal with the nonstationary and nonlinear nature of the gold price data. The former was first applied to the decomposition of time-series data of gold price into a number of components. Then, GRU was applied to the prediction of the components. To end with, all the components' prediction results were summed up to attain the final prediction result. The efficiency of the developed model was evaluated using real-world gold data, which confirmed its superiority over the standard methods used for comparison.

Keywords: Forecasting, Deep learning, Decomposition

1. Introduction

For money managers and investors to evade choosing when to supply gold, it is important to predict the upcoming tendency of the prices of this commodity. Gold reserves are normally upheld by central banks of countries to assure their shareholders' money, the currency holders, and foreign-debt creditors. Additionally, these banks use gold treasury for the management of inflation and supporting economic standing of their corresponding countries. It is well acknowledged that gold always has a significant impact on reserve assets. Particularly because of the escalating trade war between the United States and China in recent years, the international situation has endured complicated and deep changes. To manage such situation effectively, there is a need for mitigating international financial risks and preserving the stability of economy. Many reports have indicated a surge in central banks' demand for gold. For example, in 2021, totally 463 tons of gold was added to central banks gold reserve, which shows 82% increase compared to 2020. This caused the global gold reserves of central banks to reach the highest level in around 30 years. Remember that the gold price trend considerably differs from other minerals [1]; it is generally under the influence of several factors, for instance, inflation, supply and demand, and political situations. Such condition has brought about a big challenge in predicting gold price. As a result, different methods, especially AI-based methods, have been proposed in the literature to ease such challenge and offer an effective solution to this problem.

Recently, different deep learning methods have been proposed to solve various real-world prediction problems. Among all, time-series forecasting is a widely-used method

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that deals with the noisy and chaotic nature of time-series forecasting problem in a way to offer predictions of higher accuracy.

In time series forecasting in the financial context, integrating deep learning model and frequency decomposition algorithm can enhance the accuracy of prediction results. Numerous researchers have tested this combination to solve prediction-related problems. The VMD-ICA-GRUNN algorithm was developed by E, Ye, and Jin for the prediction of gold price, whose obtained results offered a high degree of precision [2]. In another study, the CEEMDAN-LSTM method was applied by Zhou et al. to forecasting carbon price. They obtained prediction results of acceptable stability and reliability, with MAPE = 0.555% and R^2 = 0.982. The findings of these studies confirmed that the analysis capacity of deep learning for decomposed time series is higher than that for undecomposed ones [3]. This is because highly volatile and non-stationary time series are decomposed into low-volatility stationary time series that can be analyzed and predicted more easily. In addition, it shows that the hybrid model is able to avoid the weaknesses of the deep learning model [4].

The current study aims to propose a model capable of accurately predicting gold price and its movement. To do this, this paper uses the decomposition-forecast-mergence scheme for the prediction of the international gold price, and proposes the hybrid "ICEEMDAN-GRU" model. The results of the experiments conducted in this study showed that the above-noted scheme and the hybrid model were able to considerably enhance the precision of predictions in this regard.

The remainder of the paper is organized as follows: Section 2 reviews the studies recently carried out on gold price prediction. Then, Section 3 explains the hybridization of the ICEEMDAN method and the GRU model, and introduces the key steps of the hybrid ICEEMDAN-GRU model. Next, Section 4 presents the experimental results and compares the prediction accuracies of different relevant models. Finally, Section 5 concludes the whole study.

2. Related work

Machine learning and deep learning methods have considerably developed during the last decade to predict gold price and movement. These methods then became highly popular in both the industrial and scientific communities. They could provide valuable outcomes regarding how prices behave. The following paragraphs summarize the findings of some outstanding studies that have introduced approaches to the prediction of gold price and its movement.

The authors in [5] examined the fluctuations of gold price, and indicated that economic variables, e.g., the inflation rate variety and the stock price stability, could be used to explain the movements in gold price. In [6], the authors found that a high gold price drives the cash flow into the gold market. They proposed a model for the prediction of the gold price trend. Then, they suggested several technologies available for the analysis and prediction of gold price. The researchers in [7] examined how the investors' expectations and general economic conditions affect the S&P 500 index and the prices of gold futures; they modeled these prices in the form of a neural network. Their study pioneered the use of the neural network for the gold price prediction. After that, several neural network-based methods were successfully proposed in the literature for the forecast of gold prices. For example, in [8], the Rolling Neural Network and the Recursive Neural Network were analyzed as two new versions of conventional neural networks and then applied to predicting variations in gold prices. In another research [9], the capacity the Adaptive Network Fuzzy Inference System (ANFIS) model was examined in terms of capturing the changes occurring to the gold price. The performance of the model was then assessed by comparing it with the performance of the Autoregressive Integrated Moving Average (ARIMA) and ANN. Their findings demonstrated the effectiveness of ANN and ANFIS in modeling the price of gold and generating results of higher quality compared to ARIMA. In [10], artificial neural networks (ANNs) and LSTM models were used to predict the daily fluctuations in gold price. They finally reported that it is highly complex to accurately predict gold prices; this difficulty, they believe, is because of many random factors that influence this material's price. Therefore, they strongly recommended considering the advice of trading experts, rather than a decision support system. The authors in [11] applied extreme learning machine to predict gold prices. Their proposed GA-based model, called regularized online sequential extreme learning machine (ROS-ELM), was employed for the optimization of its weight matrix. Using the Akaike informative criterion (AIC), they made a comparison between the performance of their proposed model and some standards models, for instance back-propagation, ARIMA, and support vector machine. The comparative results showed that their proposed model outperformed the others regarding the root-mean-square error. In [12], the CNN-LSTM model was developed to accurately forecast gold prices and its movements. Their model's first component is a convolutional layer and a pooling layer, in which complicated mathematical operations are executed for the development of the features of the input data. Then, the second component makes use of the produced LSTM and the dense layer's features. Their findings indicated that different. hyperparameters of their model are with high sensitivity and complexity; therefore, with the use of some additional optimization configurations and major feature engineering, the predictive power could be further enhanced. The researchers in [13] proposed an innovative model, ICA-GRUNN, through integrating the Gate Recurrent Unit Neural Network (GRUNN) model with a separation technique, i.e., the independent component analysis (ICA). They pointed out that three parameters, i.e., cyclic recurrent elements, stochastic factors, and long-term trend, have impact on gold prices. ICA-GRUNN first uses the ICA algorithm for the identification of the hidden influence factors from among the data available. Afterwards, it employs GRUNN for the exploitation of each independent component (IC). Finally, the gold price prediction result appears as a combination of prediction results of all ICs. The experiments conducted in their study used the data gathered from monthly gold prices in the period of time from Jan 1979 to Dec 2017. In addition, they assessed the performance of their by comparing it with that of LSTM, radial basis function (RBF), ARIMA, and neural network. As indicated by the numerical experiments results, ICA-GRUNN showed the highest prediction capability among the others. In another research [14], for the prediction of monthly gold prices, wavelets and support vector machine (SVM) were combined with each other in a single model. The feature space of the proposed integrated model comprised variables for exchange rates, interest rates, stock prices, and commodity prices. Each of these predictors were treated with the wavelets to produce additional features for SVM. The wavelet SVM succeeded to predict gold price more accurately than other models such as random forest, SVM, or boosting. In [15], the influencing factors on the gold price were analyzed using ICA and ensemble empirical mode decomposition (EEMD). The findings showed global GDP and consumer price index (CPI) as two factors that impact the gold price fluctuations in varying degrees. In [16], the ICEEMDAN-LSTM-CNN-CBAM model was configured with the use of the gold price as the object of study. ICEEMDAN was initially applied to decomposing the gold price dataset into individual IMF components, and after that, the LSTM-CNN-CBAM model to predicting the individual IMF components. At the final step, the proposed model's performance was compared to that of 11 commonly-used models in the literature, e.g., CNN-LSTM and LSTM. The results showed a significant enhancement in the accuracy level when the signal processing approach was adopted. Moreover, their proposed model was confirmed to be more successful than the others in terms of accuracy in predicting gold prices.

3. Materials and methods

3.1 Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN)

EMD [17] is an adaptive time-frequency analysis method applicable to solving the problem of mode mixing. The problem can be also solved using EEMD [18], but with a high computational cost and also residual noise in the reconstructed signals. To manage these two drawbacks, complementary ensemble empirical mode decomposition (CEEMD) was proposed in [19]. Remember that in both EEMD and CEEMD, incorrect components may be generated [20]. Although these problems can be solved by using CEEMDAN, this latter has its own drawbacks [21], which caused the ICEEMDAN method to be proposed by the authors in [22]. In the course of post processing, ICEEMDAN can be used for the decomposition of the residual-error series into a number of sub-series that can be used conveniently to forecast the error series. Figure 10 shows the decomposition results. In the following, the steps involved in ICEEMDAN that is a model designed based on CEEMDAN are explained [22]:

(a) With the use of EMD, computing the local means of I realizations $x_i = x + \beta_0 E_1(\omega^i)$ in order to attain the first residue: $r = \left\langle M(x^i)\right\rangle$, where $\beta_0 = \varepsilon_0 std(x) / std(E(w^i))$. The $M(\cdot)$ operation generates the local mean of the signal, and wi stands for white Gaussian noise with a zero mean and unit variance.

(b) At the first stage $(k = 1)$, calculating the first mode: $IMF_1 = x - r_1$.

(c) Estimating the second residue as the average of the local means of the realizations $r_1 + \beta_1 E_2(w^i)$ and defining the second mode: $IMF_2 = r_1 - r_2 = r_1 - \left\langle M(r_1 + \beta_1 E_2(w^i))\right\rangle$

(d) For $k = 3, \ldots, K$, computing the kth residue

$r_k = \langle M(r_{k-1} + \beta_{k-1} E_k(w^i)) \rangle$, and the kth mode: $IMF_k = r_{k-1} - r_k$.

(e) Repeating step (d) for the next k stages.

3.2 Gated recurrent units (GRUs)

GRU was developed by Cho et al. [23] as one of the RNN variants. GRU introduces gating structure and, this way, solves the problem with RNN due to the difficulty in dealing with long-distance information acquisition. GRU is simpler than LSTM; the former only introduces update gate (z_t) and reset gate (r_t). In this model, (z_t) (input) determines the amount of input (x_t) and previous output (h_{t-1}) that can be passed to the subsequent cell. On the other hand, (r_t) determines the amount of the past information to forget. The current memory content makes sure that only the relevant information requires to be passed to the subsequent iteration, which is determined using the weight W. The following formula governs the major operations in GRU:

Update gate:

$$z_t = \sigma\left(W_z * [h_{t-z}, x_t]\right) \tag{1}$$

Reset gate:

$$r_t = \sigma\left(W_r * [h_{t-z}, x_t]\right) \tag{2}$$

When the gate gets reset and then updated, then the GRU unit's candidate status value will be $(\tilde{h}_t)$ and the final output status value will be (h_t):

$$\begin{aligned} \tilde{h}_t &= \tanh\left(W_{\tilde{h}} * [r_t, h_{t-1}, x_t]\right), \\ h_t &= (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t. \end{aligned} \tag{3}$$

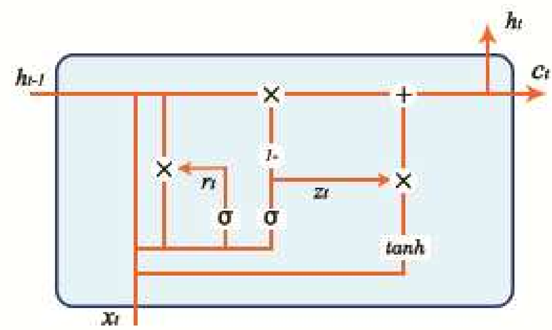

Fig. 1. Gated recurrent units

4. Proposed hybrid model

The current research aims to propose a hybrid model, containing ICEEMDAN and GRU, to predict gold price. Therefore, ICEEMDAN was used to decompose the original data into a number of components, each of which had different characteristics. Fig.4shows the output obtained after the ICEEMDAN decomposition. Then, the GRU prediction method was used to forecast the components as it is capable of properly predicting the periodic patterns in time series data. To end with, to attain the final prediction result, the prediction results of all the components were summed up. Fig.2illustrates the flowchart of the proposed scenario.

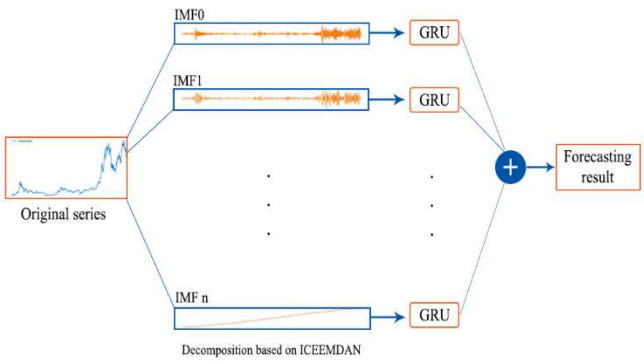

Fig. 2. Proposed hybrid model

5.Experiment and results

The present section explains the experiments conducted in this study and also the relevant analyses performed to evaluate the performance quality of the proposed hybrid model in forecasting gold price. The experiments were executed by means of the Python language using the Google Colab platform. For the purpose of this paper, the required data were gathered from www.yahoo.com for 1400trading days (the daily closing prices of the gold) ranging from Jan 02, 2018 to June10, 2023. The collected data were separated first into two sets: training (80% of data) and testing (20%). The data in the former were applied to determining the weights and threshold values of the prediction models, whereas those in the latter to assessing the developed models' performance. For the verification of the models' efficiency, the closing price of the gold given in Fig.3 was considered, assuming that the gold price of one day is continuous and related to the its prices during the last 30 days.

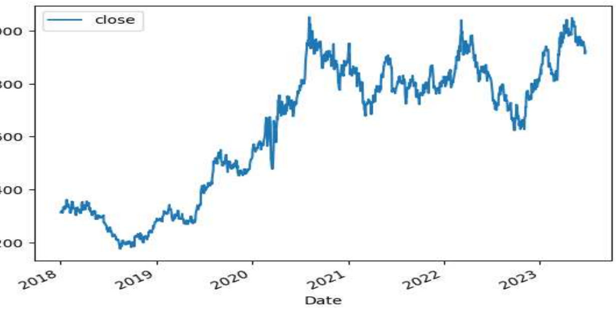

Fig. 3. Daily closing price of the gold

Considering both the existing literature and the experiments carried out so far, the GRU forecasting model (which has shown an acceptable performance) was selected in this paper. For the selection of a proper time step, various time steps were set for comparison purposes. With setting a proper time step, the error significantly drops, hence enhancing the accuracy level. Based on the experiment results, the optimum prediction accuracy was attained with setting the time step to 30days. Various hidden neurons of GRU were taken into account, with candidate values of 16, 32, 64, and 128. The results showed the GRU of 128 hidden neurons as the optimal condition. As a result, a one-layer GRU containing 128 hidden neurons was used in this study. In addition, Adam was used as the GRU optimizer due to its high computational efficiency and effectiveness. To establish a rapid computation, the batch size and the epochs were fixed at 16 and 100, respectively. Moreover, the learning rate of GRU was fixed at 0.001. Each experiment was run for 25 times and the value obtained in average was noted as the final result.

5.1 ICEEMDAN decomposition

This experiment was carried out to examine how the decomposition method affects the signals' complexity. To do this, ICEEMDAN was used for the decomposition of the original gold prices; Fig.4displays the obtained results indicating that the original data were decomposed into nine components, more specifically, eight IMFsand a residual in the top-to-bottom order. As demonstrated by Fig.4,the components' complexity and frequency start to gradually decline from top to bottom, the changing pattern is more straightforward than that of the original sequence, and the general price trend is more clear.

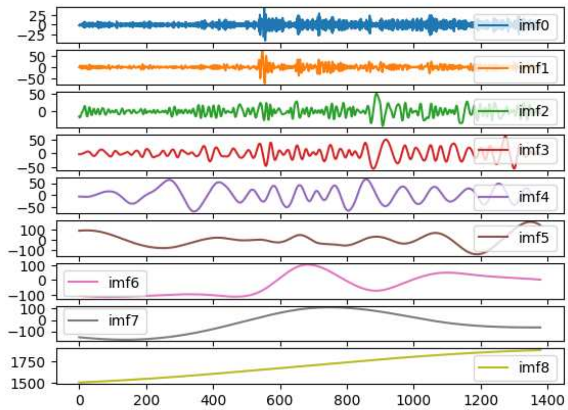

Fig. 4. Decomposition result using ICEEMDAN

5.2 Experiment 1

This experiment was executed in order to investigate how the decomposition methods affect the accuracy of predictions. To this end, initially, the original signal was decomposed into a number of components using ICEEMDAN; after that, different predictors were used to predict the resulting components. For the evaluation of the proposed model's (ICEEMDAN-GRU) efficiency, its performance was compared to the performance of Linear Regression (LR), RF, SVR, LSTM, GRU, CEEMDAN-RF, and CEEMDAN-LSTM regarding the accuracy in forecasting price. As shown by the results given in Table 1, GRU had the best performance among single models, i.e., those without decomposition. Though, the table shows that the decomposition-based models are capable of enhancing the prediction accuracy and minimizing error more than single models. The reason is that the patterns could be extracted better and the prediction accuracy could be enhanced with decomposing a non-stationary signal into a number of relatively stationary components. In addition, the obtains results showed that the proposed model could attain the best results with MAE and R2 of 8.07 and 0.99, respectively.

Table 1. The forecasting results using different methods

Methods	R2	RMSE	MAE	MAPE
ANN	0.94	19.65	14.97	0.81
LR	0.95	17.54	12.99	0.71
SVR	0.91	25.48	19.37	1.07
RF	0.93	22.76	16.92	0.93
LSTM	0.95	18.72	14.09	0.77
GRU	0.95	18.60	13.89	0.76
CEEMDAN-RF	0.98	11.34	8.71	0.48
CEEMDAN-LSTM	0.98	10.82	8.45	0.46
CEEMDAN-GRU	0.99	10.27	8.07	0.44

6. Conclusion

The prediction of gold price is not an easy task since the corresponding time series is both non-stationary and nonlinear. The present paper proposed a hybrid model concentrating on these two complexities in a way enhance the accuracy in forecasting gold price. To do this, first, the gold data were decomposed into several components by means of ICEEMDAN. After that, GRU was used to predict the components. To end with, all the components' prediction results were summed up in order to achieve the final result. Finally, for the evaluation of the proposed model's efficiency, a number of experiments were executed; the obtained results confirmed the superiority of the proposed model over the benchmark methods in terms of the accuracy in the gold price prediction.

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