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Forecasting carbon price using empirical mode decomposition and evolutionary least squares support vector regression

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HIGHLIGHTS

- A multiscale least squares support vector regression is built to predict carbon price.
- Carbon price is decomposed into several simple modes via empirical mode decomposition.
- Evolutionary least squares support vector regression is used to forecast each mode.
- The proposed approach can achieve high statistical and trading performances.

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ABSTRACT

Conventional methods are less robust in terms of accurately forecasting non-stationary and nonlineary carbon prices. In this study, we propose an empirical mode decomposition-based evolutionary least squares support vector regression multiscale ensemble forecasting model for carbon price forecasting. Firstly, each carbon price is disassembled into several simple modes with high stability and high regularity via empirical mode decomposition. Secondly, particle swarm optimization-based evolutionary least squares support vector regression is used to forecast each mode. Thirdly, the forecasted values of all the modes are composed into the ones of the original carbon price. Finally, using four different-matured carbon futures prices under the European Union Emissions Trading Scheme as samples, the empirical results show that the proposed model is more robust than the other popular forecasting methods in terms of statistical measures and trading performances.

1. Introduction

Global climate change, as a grand challenge faced by the human society, is attracting more and more attention around the world in the recent few decades. To address this challenge, the Kyoto Protocol, signed in 1997, came into effect on February 16, 2005. The protocol established the quantitative greenhouse gas emission reduction targets for the developed and industrialized countries. To achieve these targets effectively, the European Union Emissions Trading System (EU ETS) was initiated in January 2005. The EU ETS has been the biggest carbon trading market so far. It also provides an important demonstration of carbon market construction for other countries or regions, as well as a new investment choice for investors [1]. In light of this, it is important to improve the accuracy of carbon price forecasting. On the one hand, accurately forecasting carbon prices can contribute to a deep understanding on the characteristics of carbon prices so as to establish an effective and stable carbon pricing mechanism. On the other hand, it can provide a practical guidance for production operations and investment decisions, helping to avoid carbon price risks and maximize carbon assets. Therefore, carbon price prediction has become one of the most popular topics in energy research.

As we know, prediction technology generally can be classified into two categories: (i) time series forecasting, and (ii) multi-factor forecasting. Although multi-factor forecasting can consider

Abbreviations: EMD, empirical mode decomposition; LSSVR, least squares support vector regression; IMF, intrinsic mode function; PSO, particle swarm optimization; EU ETS, European Union Emissions Trading System; GARCH, generalized autoregressive conditional heteroskedasticity; ANN, artificial neural networks; ARIMA, autoregressive integrated moving average; RBF, radial basis function; ECX, European Climate Exchange; RMSE, root mean squared error; D_{stat}, directional prediction statistic; DM test, Diebold–Mariano test.

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the influences of exogenous variables, it is used to forecast the carbon price in the premise of forecasting the exogenous variables, which will inevitably lead to the problem of error accumulation so as to make the failure of carbon price prediction. Time series prediction can predict the future trend of carbon price by establishing a mathematical model to extend the trend of its own historical changeable law without the influences of exogenous variables, which can obtain a high prediction accuracy. Many studies have proven that time series prediction is applicable for energy and carbon prices forecasting. Thereby, multi-factor forecasting is excluded, and time series forecasting is utilized to predict carbon price in this study. Recently, carbon price forecasting has attracted more and more research attentions [2–11]. The time series forecasting approaches used so far can be roughly divided into two broad categories: statistical and econometric models, and artificial intelligence (AI) models. The former includes the multiple linear regression [2], GARCH [3], MS-AR-GARCH [4], FIAPGARCH [5], HAR-RV [6], and nonparametric models [7]. The latter includes artificial neural networks (ANNs) [8,9] and least squares support vector regression (LSSVR) [10,11]. Although the existing methods can obtain good results when they are applied for stationary time series forecasting, they are not robust for forecasting accurately carbon price due to its highly non-stationary and nonlinear characteristics [12].

Empirical mode decomposition (EMD), proposed by Huang and his co-authors in 1998, is an effective approach for handling the nonlinear and non-stationary time series [13–15]. EMD can disassemble any carbon price into several intrinsic mode functions (IMFs) plus a residue with high stability and high regularity. When the IMFs and residue are used as the inputs of ANN or LSSVR, it can improve learning efficiency and forecasting accuracy by providing better understanding and feature-capturing [11,16]. Thereby, the accuracy of carbon price forecasting can be enhanced through EMD. During the past few years, the EMD-based ANN and/or LSSVR models have been applied for time series forecasting [17–26], including carbon price forecasting [11,16]. However, the traditional back-propagation ANNs, used as the predictors, can lead to the overfitting problems. Although LSSVR, built on the structural risk minimization, can effectively solve the overfitting problem [27], the performance of a LSSVR predictor is sensitive to its own model selection. Yet the hybrid EMD and LSSVR models have rarely been employed for carbon price forecasting. Thus, this study seeks to address this gap in carbon price forecasting methodology.

The aim of this study is to develop an EMD-based evolutionary LSSVR model to forecast carbon prices with high accuracy. The contributions of the study are twofold. On the one hand, an EMD-based evolutionary LSSVR model (EMD–LSSVR–ADD) is constructed to forecast carbon prices: (1) each carbon price is decomposed into several IMFs plus a residue with high stability and high regularity via EMD; (2) all the IMFs and residues are respectively predicted via LSSVR trained by particle swarm optimization (PSO); (3) the forecasted values of all the IMFs and residues are aggregated into the ones of the original carbon price. On the other hand, using the empirical data from four different-matured carbon futures under the EU ETS, the study compares the forecasted results of the proposed model with the single ARIMA and LSSVR models, the hybrid ARIMA + LSSVR model, and a variation of the forecasting model (EMD-ARIMA-ADD) to demonstrate its robustness. Guo et al. [28] argued that it may be more suitable to integrate all IMFs without IMF_1 when forecasting wind speed. Thus the study adds two models by removing the IMF_1 from EMD–ARIMA–ADD and EMD–LSSVR–ADD to test whether this approach is feasible in the prediction of carbon prices, denoted as EMD–ARIMA–IMF_1–ADD and EMD–LSSVM–IMF_1–ADD models respectively. The study adopts the well-established evaluation criteria, including level forecasting, directional prediction, the Diebold–Mariano (DM) test, the Rate test, and trading performances including the Annualized return, Annualized volatility and Information ratio, to assess the robustness of the proposed EMD–LSSVR–ADD model.

The paper is organized as follows. Section 2 describes the EMD, LSSVR, and the proposed models. Section 3 reports the empirical analysis, and Section 4 concludes the study.

2. Methodology

2.1. EMD

EMD can decompose a carbon price into several IMFs and one residue by its local feature scales, as follows:

Step 1: Find out the local extreme points of carbon price $x(t)$;
Step 2: Shape the upper and lower envelopes, $e_{\max}(t)$ and $e_{\min}(t)$, respectively;
Step 3: Obtain the mean of $e_{\max}(t)$ and $e_{\min}(t)$:

$$a(t) = [e_{\max}(t) + e_{\min}(t)]/2$$

Step 4: Get the difference between $x(t)$ and $a(t)$:

$$d(t) = x(t) - a(t)$$

Step 5: Check $d(t)$. When $d(t)$ cannot meet the two conditions of IMF, let $x(t) = d(t)$, return to the step 1, and cannot repeat unless $d(t)$ meets the two conditions. Otherwise, $d(t)$ is defined as an IMF, and let the residue $r(t) = x(t) - d(t)$;
Step 6: Perform the steps 1–5 only when the termination criterion is met. In this study, we use the termination criterion proposed by Rilling et al. [29], in which $\alpha = 0.05$, $\theta_1 = 0.05$, and $\theta_2 = 0.5$.

Finally, we can obtain:

$$x(t) = \sum_{i=1}^{m} IMF_i(t) + R_m(t)$$

where m is the number of IMFs, and $R_m(t)$ is the final residue.

2.2. LSSVR

For data $\{x_i, y_i\},\ i = 1, 2, \ldots, n$, LSSVR is defined as [27]:

$$\min\left\{\frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{n}\xi_i^2\right\}$$

$$\text{s.t. } y_i = \omega \cdot \varphi(x_i) + b + e_i, \quad i = 1, 2, \ldots, n$$

in which ω: the weight vector, C: the penalty parameter, ξ_i: the error, φ: mapping function, and b:the bias.

The Lagrange function is used to find out the solutions for ω and ξ_i:

$$L(\omega, b, \xi, \alpha) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{n}\xi_i^2 - \sum_{i=1}^{n}\alpha_i\{\omega \cdot \varphi(x_i) + b + \xi_i - y_i\}$$

in which $\{\alpha_i,\ i = 1, 2, \ldots, n\}$ are a set of Lagrange multipliers. The optimal solutions are obtained from:

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{n}\alpha_i\varphi(x_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{n}\alpha_i = 0 \\ \frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = Ce_i \\ \frac{\partial L}{\partial \alpha_i} = 0 \rightarrow \omega \cdot \varphi(x_i) + b + e_i - y_i = 0 \end{cases}$$