Oil Price Forecasting Using Supervised GANs with Continuous Wavelet Transform Features

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Abstract—This paper proposes a novel approach based on a supervised Generative Adversarial Networks (GANs) model that forecasts the crude oil prices with Adaptive Scales Continuous Wavelet Transform (AS-CWT). In our study, we first confirmed that the possibility of using Continuous Wavelet Transform (CWT) to decompose an oil price series into various components, such as the sequence of days, weeks, months and years, so that the decomposed new time series can be used as inputs for a deep-learning (DL) training model. Second, we find that applying the proposed adaptive scales in the CWT method can strengthen the dependence of inputs and provide more useful information, which can improve the forecasting performance. Finally, we use the supervised GANs model as a training model, which can provide more accurate forecasts than those of the naive forecast (NF) model and other nonlinear models, such as Neural Networks (NNs), and Deep Belief Networks (DBNs) when dealing with a limited amount of oil prices data.

I. INTRODUCTION

Oil price forecasting has many implications for the economic growth of countries as well as providing useful information that helps international investors to diversify risk. According to BP’s Statistical Energy Outlook, crude oil is a vital fuel, accounting for 32.9% of global energy consumption in 2016, and will continue to play an important role until 2035. It is generally accepted that the oil price fluctuations have a significant influence on macroeconomic aggregates, such as the GDP and inflation of oil-exporting and -importing countries, as one of the most actively traded commodities in the world [1]. Thus, it is important to focus on improving the forecasting accuracy of oil prices for both real economy and financial markets. However, oil price forecasting is rather challenging because the crude oil prices are usually considered to be a nonlinear and non-stationary time series, and are interactively affected by many factors.

Research on crude oil price forecasting has lasted for decades, with many machine learning techniques being utilized to mine the inner complexity of oil prices. Among these approaches, neural networks (NNs) have been commonly used because NN models can create a breakthrough opportunity in the analysis of the non-linear behavior of the crude oil prices [2], [3]. For example, Moshiri et al. [4] compared linear economic models (ARMA and GARCH) with nonlinear NN models, and found that NNs are superior and provide a more statistically significant forecasting. Wang et al. [5] forecast monthly prices by using an NNs-based model, and claimed superior performance by the model. However, shallow architecture models, such as the the NN-based forecasting models mentioned above, cannot model the complex patterns and volatile behaviors of oil prices, which are influenced by numerous factors (Bengio et al. [6]).

Recently, the deep-learning (DL) approach is becoming a mainstream of machine learning technique, and has dramatically improved the performance of various nonlinear modeling tasks due to the multi-layers architecture. Hinton et al. [7] proposed a greedy layer-wise training strategy which solves the training problem in deep neural networks (DNNs). And, Yu et al. [8] have applied the DL approach to the oil price forecasting. However, there are two problems for oil prices forecasting when using the DL models. First, deep learning models are restricted to problems with moderate dimensions for training data. The original oil price is a one-dimensional sequence that is not suitable for DL approaches. Thus, the oil price data need to be transformed to high dimensional data before training the DL models. Second, DL models need sufficient data for training. But, compared with the size of training data used in speech signal processing or image processing tasks, the oil price data is insufficient for DL models.

In this paper, to overcome the two problems mentioned above, we propose a novel method that uses adaptive scales CWT (AS-CWT) to decompose one dimensional oil price data to high-dimensional features, and then train them with the supervised GANs model.

Wavelet analysis has recently been used in the economic fields of time-series analysis, such as business cycle synchronization, commodities, and to study the co-movement among financial markets. In oil price forecasting, Jammazi et al. [9] combined the wavelet transform and a NN to forecast the crude oil monthly price. Tang et al. [10] constructed a multiple-wavelet recurrent NN model to analyze crude oil monthly prices. Different from these papers, which predict the monthly oil prices, in our paper, we aim to forecast the daily oil price series by using the AS-CWT method with supervised GANs models. The proposed AS-CWT method can systematically capture the oil prices of different temporal scales by using adaptive scales, which can then represent different oil prices levels ranging from daily prices to yearly prices levels, but better optimized.