FORECASTING CRUDE OIL PRICE VOLATILITY USING NONLINEAR NEURAL NETWORK AUTOREGRESSION (NNAR) MODELS

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Abstract. *This paper examines the forecasting of crude oil price volatility using the Nonlinear Neural Network Autoregression (NNAR) model based on daily data from 2018 to 2026. Given the high volatility and complex dynamics of energy markets, traditional linear models often fail to capture structural shifts. The empirical results demonstrate that the estimated NNAR(31,1,16)[5] model effectively captures nonlinear patterns and delivers robust short-term point forecasts, offering valuable insights for energy market risk management.*

Keywords: *Crude Oil Market, Volatility Forecasting, Neural Network Autoregression, Nonlinear Dynamics.*

Crude oil remains one of the most critical and strategically vital commodities in the global economy (Zheng et al., 2025). Its price movements directly influence macroeconomic stability, inflationary pressures, and the operational performance of financial markets worldwide. However, the international crude oil market is notoriously volatile, driven by a complex interplay of geopolitical tensions, sudden supply-demand disruptions, and speculative market behaviors (Cheng et al., 2019).

Among various machine learning tools, Neural Network Autoregression (NNAR) has emerged as a powerful framework capable of mapping intricate, nonlinear dependencies without requiring strict a priori assumptions about the data-generating process (Hyndman & Athanasopoulos, 2018).

Hsieh (1989) and Granger and Teräsvirta (1993) provided foundational evidence that financial and economic time series frequently exhibit significant nonlinear dependencies. Traditional linear specifications, such as the Autoregressive Integrated Moving Average (ARIMA) framework, assume a linear data-generating process and often struggle with structural breaks, regime shifts, and asymmetric responses.

The Neural Network Autoregression (NNAR) model combines traditional autoregressive time-series structures with a single-hidden-layer feed-forward neural

network. An NNAR(p, P, k)[m] model is defined by non-seasonal lags (p), seasonal lags (P), hidden nodes (k), and seasonal frequency (m).

The model predicts future values ($\hat{y}$) based on past lagged observations through a neural network function f:

$$\hat{y} = f(y_{t-1}, y_{t-2} \cdots, y_{t-p}, y_{t-m}, y_{t-2m}, \cdots, y_{t-pm}).$$

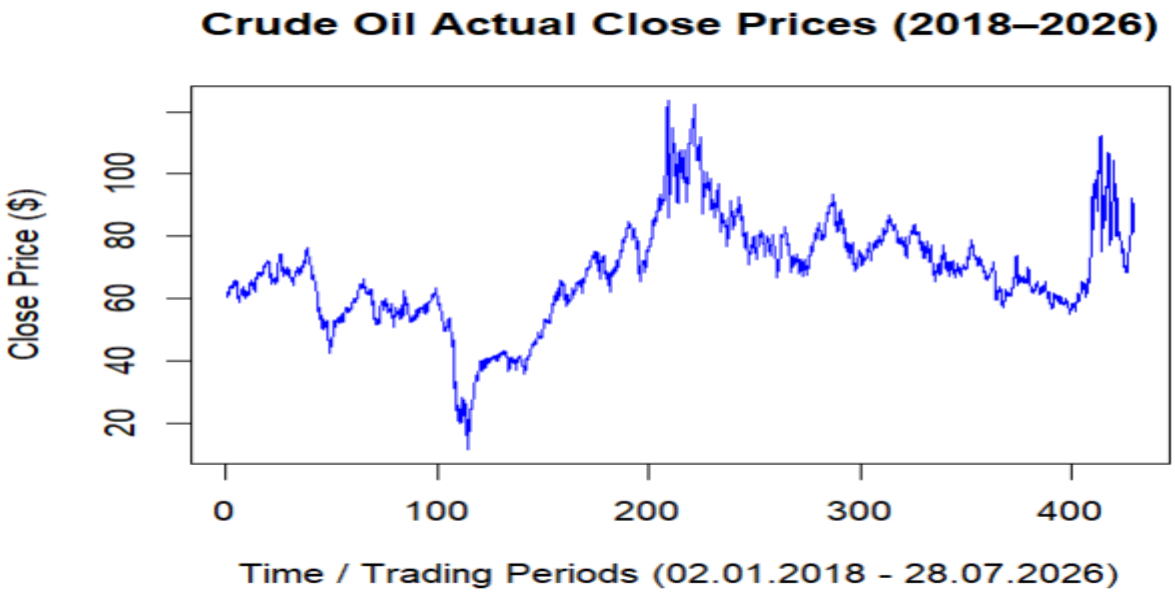


Figure 1. Compiled and visualized daily historical crude oil closing price data (January 2, 2018 – July 28, 2026) retrieved from Google Finance.

During the research, based on daily crude oil price data from January 2, 2018, to July 28, 2026, the artificial neural network-based **NNAR(31,1,16)[5]** model was optimized and applied in practice.

Table 1.

Short-term out-of-sample crude oil price forecast based on the NNAR(31,1,16)[5] model

Date	Forecasted Price	Date	Forecasted Price
2026-07-29	83.45630	2026-08-05	84.21822
2026-07-30	84.01867	2026-08-06	84.97087
2026-07-31	82.50812	2026-08-07	85.56871
2026-08-03	82.70563	2026-08-10	85.87481
2026-08-04	83.27133	2026-08-11	86.94161

The 10-day short-term out-of-sample forecast generated by the NNAR(31,1,16)[5] model reveals a steady upward trajectory in crude oil prices, followed by minor market stabilization.

The study successfully applied the **NNAR(31,1,16)[5]** model to forecast crude oil prices using daily data from 2018 to 2026. The results demonstrate that neural network models effectively capture complex, nonlinear market dynamics and deliver reliable short-term out-of-sample predictions.

- Risk Management: Integrate NNAR models into corporate and financial hedging strategies to mitigate commodity price volatility risks.
- Model Enhancement: Explore advanced hybrid architectures (such as combining neural networks with volatility models) for extended forecasting horizons.
- Strategic Planning: Utilize machine-learning price forecasts for energy security and macroeconomic policy formulations.

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