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Price forecasting through neural networks for crude oil, heating oil, and natural gas

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ABSTRACT

Building price projections of various energy commodities has long been an important endeavor for a wide range of participants in the energy market. We study the forecast problem in this paper by concentrating on four significant energy commodities. Using nonlinear autoregressive neural network models, we investigate the daily prices of WTI and Brent crude oil as well as the monthly prices of Henry Hub natural gas and New York Harbor No. 2 heating oil. We investigate prediction performance resulting from various model configurations, including training techniques, hidden neurons, delays, and data segmentation. Based on the investigation, relatively straightforward models are built that yield quite accurate and reliable performance. Specifically, performance in terms of relative root mean square errors is 1.96%/1.81%/9.75%/21.76%, 1.96%/1.80%/8.76%/14.41%, and 1.87%/1.78%/9.10%/16.97% for model training, validation, and testing, respectively, and the overall relative root mean square error is 1.95%/1.80%/9.51%/20.35% for the whole sample for WTI crude oil/Brent crude oil/ New York Harbor No. 2 heating oil/Henry Hub natural gas. The outcomes of this projection might be used in technical analysis or integrated with other fundamental forecasts for policy analysis.

1. Introduction

Policy makers and other players in the energy market have traditionally found it difficult to predict the pricing of energy commodities. This could be especially true when one takes into account the inherent strategic value that energy commodities often have for a nation or an area [1–3]. In the energy markets, different forecast users seek price projections. For instance, they give valuable insights into how energy plants should set their future sales prices, give trading partners the information they need to meet their contractual obligations, highlight potential profit-seeking opportunities in the spot and futures markets, and alert policymakers to potential gaps in risk management and policy assessments [4]. Given that price volatilities are often rather erratic [5,6] and that price levels have a significant influence on business and regulatory decisions, as well as resource allocations and societal welfare [7,8], price forecasting's importance to the energy industry shouldn't require much incentive.

In the literature on applied econometrics, one approach that has been taken is the use of time-series models to construct stable and reliable forecast outcomes for commodity prices [9–12]. Typical models that have been sought after in earlier research include the VAR (vector autoregression), VEC (vector error correction), and ARIMA (autoregressive integrated moving average) models. The univariate ARIMA model often depends on historical data for the variable that has to be predicted. As another widely used econometric forecasting method, the VAR is based on the relationships between examined economic variables rather than using a single source of data for predicting. In contrast to the VAR, the VEC model is based on the theory of cointegration, which is employed to further integrate long-term correlations between the economic variables under investigation. Generally speaking, long-term price forecasting jobs are where the VEC model shines.

In the last ten years, there has been a significant decrease in the cost of computing power, and there has been a documented interest among researchers in developing machine learning models to provide accurate financial and economic forecasts [13–16]. This includes, of course, forecasts of commodity prices related to the energy market [17–40, 41–60,61–85,86–102], such as those for natural gas [25,54,84,86–105], heating oil [82–85,102], and crude oil [18–30,31–50,51-70,71–81,84, 102,105–111]. Neural networks [20,22–31,33,35–37,39–41,45–47,49, 50,53,54,56–59,62–70,72–76,78–80,83–87,89,90,92–103,108,110], deep learning [104,105,111], boosting [18,21,38,40,57,79,87,91], regression trees [28,48,55,88], ensembles [19,23,33,42,43,57,64,65,71,

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72,74,75,88,94,95,106,109], random forests [21,25,30,40,45,70], bagging [28], extreme learning [31,33,34,52,107], multivariate adaptive regression splines [49], Gaussian process regressions [54,87,88], and support vector regressions [20,21,23,30–33,35,38,42,44–47,50,51,54,60–63,65–67,72,74,75,77,78,80–82,86–88,90,91,94,95,97,98] are some of the machine learning forecasting techniques that are frequently seen in the literature. Table 1 provides a summary of these previous studies on forecasting energy commodity prices through machine learning methods. Based on these reviews—which are not all-inclusive—it seems that one of the best methods for creating price projections for energy commodities is the neural network model. More precisely, a wide range of chaotic and noisy time-series variables [112–116], such as various financial and economic time series [117–119], may be accurately predicted using the neural network model. This may be due to the neural network model's strong capacity for self-learning [81] and describing nonlinear properties [120] in a variety of time series. In this instance, we utilize neural networks to estimate four significant energy commodity price indices: Henry Hub natural gas, West Texas Intermediate (WTI) crude oil, Brent crude oil, and New York Harbor No. 2 heating oil.

The four energy commodities listed above were chosen for examination primarily because of their strategic or economic value to the community. For instance, two of the three primary benchmarks used in oil pricing are WTI and Brent crude oils; Dubai crude oil is the third. Both WTI and Brent crude oil are light, sweet, and of excellent quality; the former is mostly obtained from interior Texas, while the latter is derived from the North Sea. Both are easy to process. The benchmark for almost two thirds of the worldwide oil contracts is Brent crude oil, while WTI crude oil is the underlying commodity for oil futures contracts on the New York Mercantile Exchange (NYMEX). When compared to Brent crude oil, WTI crude oil is typically sold at a discount. About one-fourth of a barrel of crude oil production is made up of New York Harbor No. 2 heating oil, a liquid petroleum distillate used as fuel in boilers and furnaces. Both Intercontinental Exchange–Europe and NYMEX are venues for trading its futures contracts. NYMEX futures contracts are sent to Henry Hub for delivery, a natural gas pipeline located near Erath, Louisiana. Henry Hub settlement prices are a component of the global liquid natural gas market and act as benchmarks for the whole North American natural gas market. Few incentives should be needed to recognize the significance of these four energy commodities.

In order to perform our analysis, we use the non-linear auto-regressive neural network technique to analyze forecast problems in data sets of daily price data for WTI and Brent crude oil over an eleven-year period, monthly price data for the New York Harbor No. 2 heating oil over a thirty-six-year period, and monthly price data for the Henry Hub natural gas over a twenty-five-year period. We evaluate the performance of predictions resulting from various model configurations, which take into account training techniques, hidden neurons, delays, and data segmentation. Based on the investigation, relatively straightforward models are built that yield quite accurate and reliable performance. More specifically, the constructed models lead to relative root mean square errors of 1.96%/1.81%/9.75%/21.76%, 1.96%/1.80%/8.76%/14.41%, and 1.87%/1.78%/9.10%/16.97% for model training, validation, and testing, respectively, and an overall relative root mean square error of 1.95%/1.80%/9.51%/20.35% for the whole sample for WTI crude oil/Brent crude oil/New York Harbor No. 2 heating oil/Henry Hub natural gas. The outcomes of this projection might be used in technical analysis or integrated with other fundamental forecasts for policy analysis.

2. Data

Daily price data for WTI Crude Oil during 09/26/2011 – 09/24/2021 ($/Barrel) and Brent Crude Oil during 09/26/2011 – 09/20/2021 ($/Barrel), and monthly price data for New York Harbor No. 2 Heating Oil during 06/1986 – 09/2021 ($/Gallon) and Henry Hub Natural Gas during 01/1997 – 09/2021 ($/Million Btu) are shown in Fig. 1, together with first differences of these price series. Fig. 1 also visualizes the price

Table 1
Previous studies on forecasting energy commodity prices through machine learning methods.

Literature	Publication year	Target variable (prices)	Methodology
[102]	2005	Crude oil, heating oil, gasoline, and natural gas	Neural network
[68]	2012	WTI crude oil and Brent crude oil	Transfer learning based model
[19]	2013	WTI crude oil	Ensemble
[35]	2013	WTI crude oil	Semi-supervised learning
[100]	2013	Natural gas of Energy Information Administration of US Department of Energy	Neural network
[62]	2014	WTI crude oil	Compressed sensing based model
[77]	2014	Crude oil	Support vector machine
[82]	2014	Heating oil	Support vector machine with enhanced Artificial Bee Colony
[85]	2014	Propane, heating oil, Kerosene type jet fuel, US coast gasoline, and New York gasoline	Neural network
[28]	2015	Crude oil	Ensemble
[32]	2015	Crude oil	Support vector machine with particle swarm optimization
[75]	2015	WTI crude oil	Ensemble
[76]	2015	WTI crude oil	Genetic algorithm neural network
[33]	2016	WTI crude oil	Extended extreme learning machine
[58]	2016	Crude oil	Genetic algorithm neural network
[61]	2016	WTI crude oil and Brent crude oil	Genetic algorithm support vector machine
[97]	2016	Natural gas	Text mining and sentiment analysis
[18]	2017	Crude oil	XGBoost
[20]	2017	Crude palm oil	Support vector machine with sequential minimal optimization
[22]	2017	WTI crude oil	Stream learning
[23]	2017	WTI crude oil	Deep learning ensemble
[41]	2017	WTI crude oil	Deep learning
[50]	2017	Crude oil	Neural network and support vector machine
[55]	2017	Crude oil	Decision tree
[86]	2017	Henry Hub natural gas	Neural network and seasonality-adjusted support vector machine
[24]	2018	Crude oil	Long short-term memory neural network
[34]	2018	Crude oil	Extreme learning machine
[44]	2018	Crude oil of Energy Information Administration of US Department of Energy	Support vector machine
[65]	2018	WTI crude oil and Brent crude oil	Ensemble
[66]	2018	WTI crude oil	Neural network and support vector machine
[69]	2018	Crude oil	Random vector functional link network

(continued on next page)

Table 1 (*continued*)

Literature	Publication year	Target variable (prices)	Methodology
[78]	2018	WTI crude oil and Brent crude oil	Random wavelet neural network
[80]	2018	Crude oil	Neural network, support vector machine, and model combination
[83]	2018	Heating oil	Neural network
[25]	2019	WTI crude oil, Brent crude oil, Dubai Fateh crude oil, US natural gas, and Russian natual gas	Neural network and random forest
[26]	2019	Crude oil	Convolutional neural network
[31]	2019	WTI crude oil	Long short-term memory neural network
[36]	2019	Crude oil	Convolution neural networks
[37]	2019	Crude oil	Multi-recurrent network
[45]	2019	WTI crude oil, Brent crude oil, and OPEC reference basket	Hybrid Bayesian network
[47]	2019	Crude oil	Long short-term memory neural network
[48]	2019	Crude oil	Decision tree
[51]	2019	WTI crude oil	Support vector machine
[54]	2019	Crude oil and natural gas	Neural network, support vector machine, and model combination
[59]	2019	WTI crude oil and Brent crude oil	Long short-term memory neural network
[63]	2019	WTI crude oil	Genetic algorithm neural network
[71]	2019	WTI crude oil	Sparse Bayesian learnin
[72]	2019	WTI crude oil	XGBoost
[73]	2019	Crude oil	Neural network
[84]	2019	Crude oil and natural gas	Double parallel feedforward neural network
[87]	2019	Henry Hub natural gas	neural network, support vector machine, gradient boosting machine, and Gaussian process regression
[89]	2019	Natural gas	Sentiment analysis
[91]	2019	Henry Hub natural gas	Least squares regression boosting
[93]	2019	Natural gas	Neural network
[101]	2019	Henry Hub natural gas	Neural network
[21]	2020	Crude oil	XGBoost
[27]	2020	Europe Brent crude oil	Ensemble
[39]	2020	Brent crude oil	Hybrid model
[42]	2020	Crude oil	Hybrid model
[46]	2020	Crude oil	Model combination
[49]	2020	WTI crude oil and Brent crude oil	Hybrid model
[53]	2020	Crude oil	Adaptive neuro-fuzzy inference system
[64]	2020	Brent crude oil	Random vector functional link network
[67]	2020	Crude oil	Hybrid neural network
[81]	2020	Crude oil	Support vector machine
[90]	2020	Natural gas	Hybrid model
[92]	2020	Northwestern European wholesale natural gas	Gradient descent and least squares optimization
[96]	2020	Natural gas	Deep learning
[99]	2020	Natural gas	Neural network
[29]	2021	Crude oil	Recurrent neural network and long-term and short-term memory model
[30]	2021	Brent crude oil	neural network, support vector machine, and random forest
[38]	2021	Indian crude oil	XGBoost and support vector machine
[40]	2021	Crude oil	Neural network, XGBoost, LightGBM, CatBoost, and random forest
[43]	2021	WTI crude oil and Brent crude oil	Extreme learning machine
[52]	2021	Crude oil	Hybrid model
[56]	2021	Crude oil	Long short-term memory network
[57]	2021	Crude oil	Random vector functional link network
[70]	2021	Nigerian Bonny light crude oil	Neural network and random forest
[74]	2021	WTI crude oil and Brent crude oil	Multiscale hybrid paradigm
[79]	2021	Crude oil	AdaBoost-LSTM and AdaBoost-GRU
[88]	2021	Natural gas	Support vector machine, regression tree, ensemble of trees, and Gaussian process regression
[94]	2021	Natural gas	Ensemble
[95]	2021	Natural gas	Hybrid model
[98]	2021	Henry Hub natural gas	Deep belief network
[106]	2022	WTI crude oil	Decomposition ensemble based deep learning
[107]	2022	WTI crude oil and Brent crude oil	Extreme learning machine
[104]	2022	Henry Hub natural gas	Deep learning
[103]	2023	Henry Hub natural gas	Temporal convolutional network
[108]	2023	WTI crude oil	Neural network
[109]	2023	WTI crude oil	Ensemble
[110]	2024	Brent crude oil	Auditory multi-feature collaboration network
[105]	2024	Oil and gas stocks	Deep learning
[111]	2024	WTI crude oil	Deep learning

data through histograms with fifty bins, as well as kernel estimates, for presenting their distributional patterns. The pricing data is summarized statistically in Table 2, and it is clear that, consistent with what is typically expected for financial series [121], the data are not normally distributed.

3. Method

For the purpose of predicting the prices of various energy commodities, such as WTI and Brent crude oils, New York Harbor No. 2 heating oil, and Henry Hub natural gas, non-linear auto-regressive neural network models are utilized. It is depicted as $y_t = f(y_{t-1}, \ldots, y_{t-d})$, where

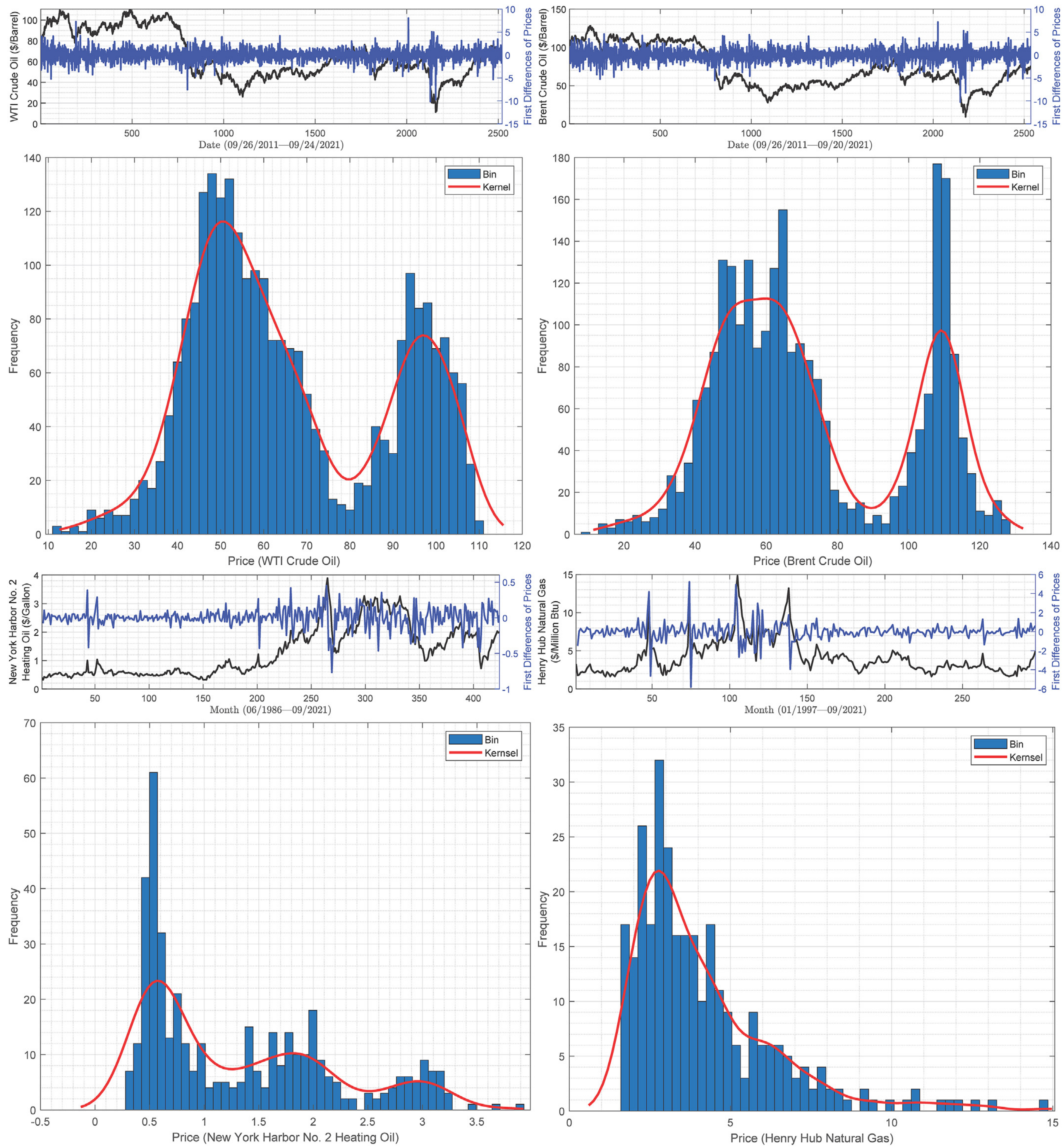


Fig. 1. Daily price time series and the corresponding first differences of the WTI crude oil and Brent crude oil, and monthly price time series and the corresponding first differences of the New York Harbor No. 2 heating oil and Henry Hub natural gas, as well as histograms with fifty bins and kernel estimates of the price data.

the price series of a particular energy commodity that will be predicted is represented by y, the function is represented by f, the number of delays is indicated by d, and time is indexed by t. The focus of the present study is on one-day (one-month) forward-looking projections for WTI and Brent crude oil (New York Harbor No. 2 heating oil and Henry Hub natural gas). Here, the model with a two-layer feed-forward network structure is used. For the output layer, it employs a linear transfer function and a sigmoid transfer function for the hidden layers. Both theoretical and empirical research on neural networks has found it intriguing to determine how many layers are required for specific tasks; nevertheless, there seem to be no clear guidelines currently from the theoretical literature on this subject [122,123]. Since training time would increase exponentially with the number of layers used (i.e., much more computation would be required) and the tendency of model overfitting would also increase, practically speaking, the neural network implementation does not typically require too many layers [123]. Decision boundaries that are rather complicated can already be formed using a two-layer network [122]. A two-layer network appears to be enough in our

Table 2
Summary statistics of daily price time series and the corresponding first differences of the WTI crude oil and Brent crude oil, and monthly price time series and the corresponding first differences of the New York Harbor No. 2 heating oil and Henry Hub natural gas.

Energy Commodity	Series	Minimum	Mean	Median	Maximum	Standard Deviation	Skewness	Kurtosis	Jarque-Bera p-value
WTI Crude Oil	Price ($/Barrel)	11.258	66.257	59.750	110.530	22.625	0.356	1.930	<0.001
	First Difference	−10.150	−0.003	0.060	8.050	1.300	−0.439	7.913	<0.001
Brent Crude Oil	Price ($/Barrel)	9.120	72.615	64.830	128.140	26.495	0.376	1.904	<0.001
	First Difference	−10.270	−0.014	0.040	7.170	1.311	−0.405	6.554	<0.001
New York Harbor No. 2 Heating Oil	Price ($/Gallon)	0.321	1.309	0.968	3.890	0.866	0.803	2.503	<0.001
	First Difference	−0.766	0.004	0.006	0.452	0.137	−0.870	6.913	<0.001
Henry Hub Natural Gas	Price ($/Million Btu)	1.610	4.150	3.480	14.840	2.229	1.750	6.750	<0.001
	First Difference	−5.800	0.006	0.025	5.230	0.978	−0.111	14.602	<0.001

specific case without many predictors. According to a seminal study [124], most issues can be solved by a neural network with no more than two hidden layers.

The final models are based on the following: two delays and two hidden neurons for Brent crude oil, three delays and eight hidden neurons for New York Harbor No. 2 heating oil, two delays and five hidden neurons for Henry Hub natural gas, and four delays and three hidden neurons for WTI crude oil. Fig. 2 visualizes the structure of the non-linear auto-regressive neural network model for each of the four commodities through the block diagram. The Levenberg-Marquardt (LM) technique [125,126] is utilized for model estimation, and the price series are divided into training, validation, and testing segments based on a ratio of 70%–15% –15%. This technique approximates second-order training speed while avoiding the calculation of the Hessian matrix [127,128]. To train models, a variety of algorithms could be tested. This work also explores the scaled conjugate gradient (SCG) approach [129], which is generally determined to be quicker than the LM technique. Numerous research domains have extensively utilized these two algorithms [130,131]. One may find their empirical and theoretical comparisons in the literature [132,133].

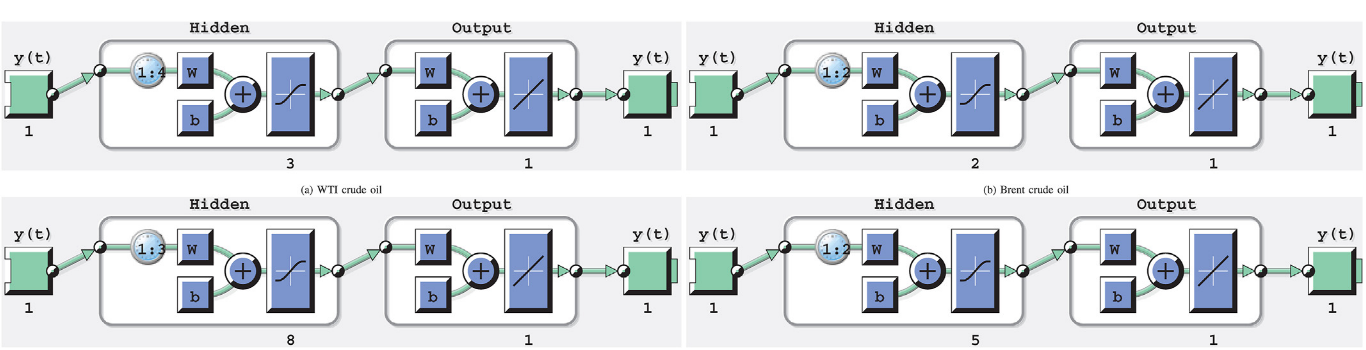
Different settings over data segmentation ratios, hidden neurons, and delays, together with training algorithms, are tested during the creation of our final models. In particular, the following are assessed: data spitting ratios of 60%–20%–20%, 70%–15%–15%, and 80%–10%–10% for training, validation, and testing; delays of 2, 3, 4, 5, and 6; and hidden neurons of 2, 3, 5, and 8. Table 3 lists all of the examined model parameters. For the WTI crude oil, Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas, respectively, the settings #15, #1, #33, and #21 are utilized to create our final models.

Table 3
Investigated model settings for daily price time series of the WTI crude oil and Brent crude oil and monthly price time series of the New York Harbor No. 2 heating oil and Henry Hub natural gas.

		Model Setting
Algorithm	LM	1+2i (i = 0,1, …,59)
	SCG	2+2i(i = 0,1, …,59)
Delay	2	1 + 10j–2+10j (j = 0,1, …,11)
	3	3 + 10j–4+10j (j = 0,1, …,11)
	4	5 + 10j–6+10j (j = 0,1, …,11)
	5	7 + 10j–8+10j (j = 0,1, …,11)
	6	9 + 10j–10 + 10j (j = 0,1, …,11)
Hidden Neuron	2	1 + 40k–10 + 40k (k = 0,1,2)
	3	11 + 40k–20 + 40k (k = 0,1,2)
	5	21 + 40k–30 + 40k (k = 0,1,2)
	8	31 + 40k–40 + 40k (k = 0,1,2)
Training vs. Validation vs. Testing Ratio	70% vs. 15% vs. 15%	1–40
	60% vs. 20% vs. 20%	41–80
	80% vs. 10% vs. 10%	81–120

4. Benchmark analysis

Neural networks will be the main subject of analysis. This study first examines four different benchmark models: the regression tree model (RT), the support vector regression model (SVR), the autoregressive model (AR), and the AR-generalized autoregressive conditional heteroskedasticity model (AR-GARCH). When analyzing forecast performance of these models under consideration, the MDM test, which stands for the modified Diebold-Mariano test [134,135], is employed to assess differences in forecast mean squared errors (MSEs) of two models being compared, in addition to the RRMSE. The basis for the MDM test is d_t =



(a) WTI crude oil
(b) Brent crude oil
(c) New York Harbor No. 2 heating oil
(d) Henry Hub natural gas

Fig. 2. Visualization of the structure of the non-linear auto-regressive neural network model for each of the four commodities through the block diagram.

$\left(\text{error}_t^{M_1}\right)^2 - \left(\text{error}_t^{M_2}\right)^2$, where $\text{error}_t^{M_1}$ and $\text{error}_t^{M_2}$ are used to denote two error terms recorded at time t that are generated through model M_1 and model M_2, respectively. In this instance, M_1 would stand for one of the four benchmark models that were evaluated, and M_2 might stand for the neural network model that we finally selected for a certain energy commodity. One way to represent the MDM test statistic is $MDM = \left[\frac{T+1-2h+T^{-1}h(h-1)}{T}\right]^{1/2}\left[T^{-1}\left(\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right)\right]^{-1/2} d$, where T is used to denote the length of the time period for carrying out comparisons of forecasting performance, h is utilized to show the forecasting horizon (here, $h = 1$), d is employed to reflect d_t's sample average, $\gamma_0 = T^{-1}\sum_{t=1}^{T}\left(d_t - d\right)^2$ is adopted to signify d_t's variance, and $\gamma_k = T^{-1}\sum_{t=k+1}^{T}\left(d_t - d\right)\left(d_{t-k} - d\right)$ is applied to represent d_t's kth auto-covariance for $k = 1, \ldots, h-1$ and $h \geq 2$. The MDM test's null hypothesis states that the MSEs generated by two distinct models are identical. The MDM test under the null hypothesis will follow a $t-$distribution with $T-1$ degrees of freedom.

Details on the four benchmark models mentioned above are provided below. The number of lags used by the AR model and the number of delays in the selected neural network model are the same for the price of each energy commodity. More specifically, the numbers of lags used by the AR models are four, two, three, and two, respectively, for prices of WTI crude oil, Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas. The AR-GARCH model uses GARCH(1,1) as the structure for the GARCH component, with the same number of lags as the number of delays in the selected neural network model. The linear $\epsilon-$ insensitive SVR model is employed, where the target variable's interquartile range is divided by 1.349 for the box constraint and the target variable's interquartile range is divided by 13.49 for the half width of the $\epsilon-$ insensitive band. The RT model makes use of the classification analysis and regression tree (CART) [136] approach, which requires a minimum of 4 data points for leaf nodes and 10 observations for branch nodes. Lagged one to lagged four, two, three, and two prices are employed as predictors for both the RT and SVR models, respectively, for WTI crude oil, Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas.

The results of benchmark analysis based on the RRMSE of the testing phase are displayed in Fig. 3 for the price of each of the four energy commodities. By contrasting the selected neural network model with the four benchmark models, it is clear that the selected neural network model is more accurate with a lower RRMSE for each energy commodity. The $p-$ value for the MDM test is less than 0.01 when the selected neural network model is compared with each of the four benchmark models for each energy commodity, suggesting that the selected neural network model outperforms the four benchmark models under consideration statistically significantly.

5. Result

For the daily price time series of WTI and Brent crude oil, as well as the monthly price time series of Henry Hub natural gas and New York Harbor No. 2 heating oil, we assess each model setting listed in Table 3. We use the relative root mean square error (RRMSE) to assess the accuracy of our forecasts, enabling the comparison of various predicted

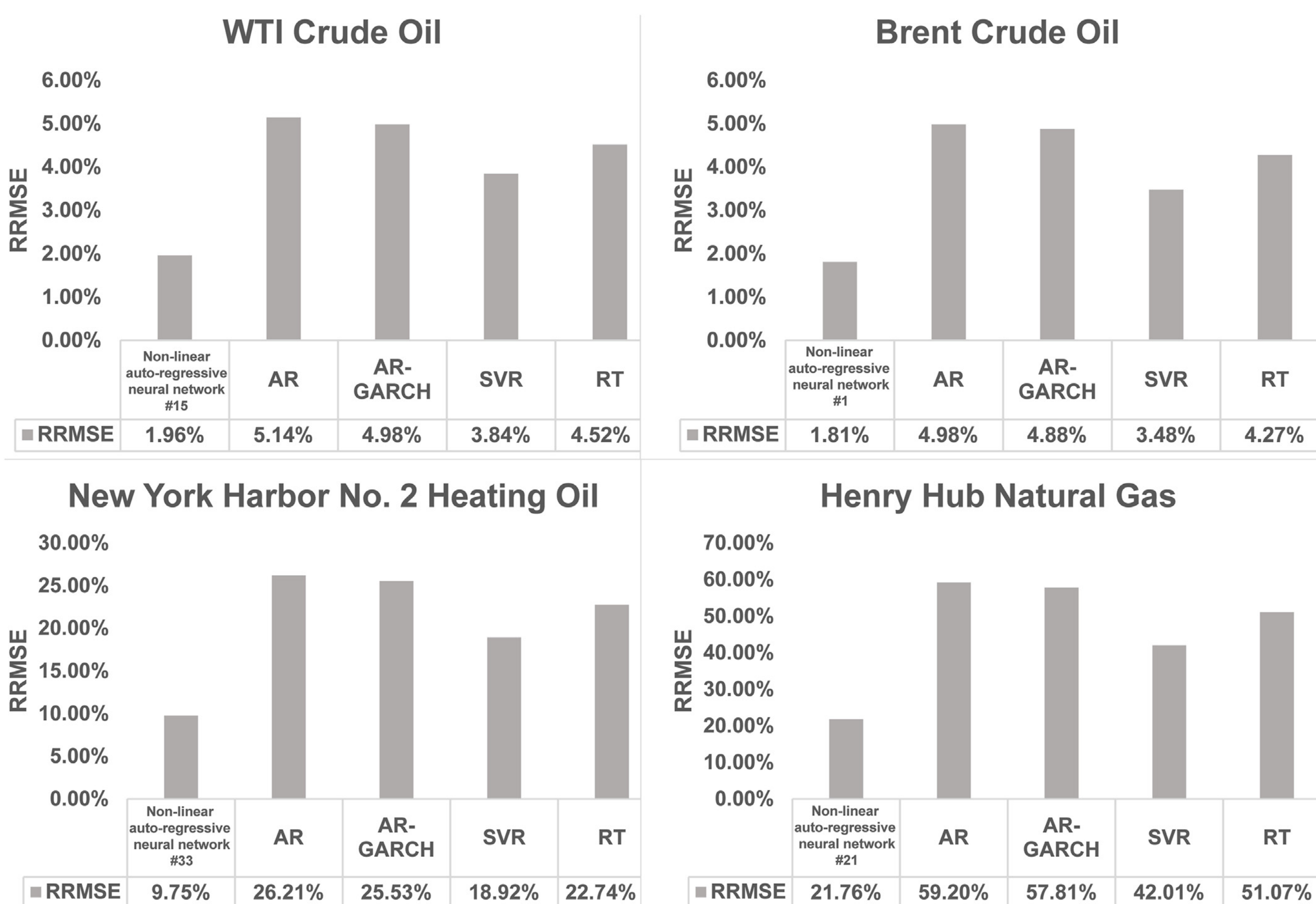


Fig. 3. Benchmark analysis: Comparisons of forecast performance for the testing phase based upon the selected neural network model and the AR, AR-GARCH, SVR, and RT models for prices of four energy commodities.

results across a range of models or targets [137–140]. Previous studies [137–140] have suggested the methods for evaluating the accuracy of model predictions, which are outlined below: excellent if RRMSE< 10%, good if 10% < RRMSE< 20%, fair if 20% < RRMSE< 30%, and poor if RRMSE≥ 30%. During the training, validation, and testing phases, we compute the RRMSEs that are produced by each model parameter. All of the RRMSEs for every commodity are shown in Fig. 4. We consider the need to balance forecast accuracy and forecast stabilities across the three phases when determining the final model setting for the price time series of each commodity. For the WTI crude oil, Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas, respectively, we choose settings #15 (four delays and three hidden neurons), #1 (two delays and two hidden neurons), #33 (three delays and eight hidden neurons), and #21 (two delays and five hidden neurons). The LM method and a data splitting ratio of 70%–15%–15% are being applied in these four cases for training, validation, and testing. More precisely, using the WTI crude oil as an example, Fig. 4 shows that, for the chosen option #15, the grey triangle for testing, the orange square for validation, and the blue diamond for training are all rather near to one another. There are some that, in contrast to the chosen setting, provide a lower RRMSE for one sub-sample but higher RRMSEs for the other sub-samples, indicating weaker stabilities. In training, for instance, the option #3 (#11) produces a lower RRMSE than the setting #15; yet, in testing and validation, the RRMSEs are greater. More specifically, the option #3 (#11) produces RRMSEs of 1.94% (1.91%), 2.00% (2.08%), and 1.93% (2.02%), respectively, for the training, validation, and testing phases, while the setting #15 generates RRMSEs of 1.96%, 1.96%, and 1.87%, respectively. In other words, the setting #15 leads to better performance stabilities from the training to validation phase than the option #3 and the setting #15 leads to better performance for the testing phase than the option #3. Thus, the setting #15 is preferable as compared to the option #3. Similarly, the setting #15 leads to better performance stabilities from the training to validation phase and from the training to testing phase than the option #11 and the setting #15 leads to better performance for the testing phase than the option #11. Thus, the setting #15 is preferable as compared to the option #11. We attempt to prevent either underfitting or overfitting by choosing the model configuration that offers comparatively consistent performance throughout training, validation, and testing.

After determining the chosen settings for the price time series of these four energy commodities, we switch between one model parameter at a time to evaluate the performance's sensitivity to other settings. The findings of evaluations of performance sensitivities for every commodity are displayed in Fig. 5, where RRMSEs for the training, validation, and testing phases are given. The performance comparison of model settings #15 and #16—the former based on the LM algorithm and the latter on the SCG algorithm—aims to assess the sensitivity to training algorithm, using the WTI crude oil as an example. In order to assess sensitivity to delays, performance comparisons are made between model settings #15, #11, #13, #17, and #19; the former is based on four delays, while the latter four are based on two, three, five, and six delays, respectively. Model settings #15, #5, #25, and #35 are compared in terms of performance in order to assess sensitivity to hidden neurons. This is because the former is based on three hidden neurons, while the later three are based on two, five, and eight hidden neurons, respectively. In order to assess sensitivity to the price series' segmentation into the training, validation, and testing phases, performance comparisons are made between model settings #15, #55, and #95. The former is based on the ratio of 70%–15%–15%, while the latter two are based on the ratios of 60%–20%–20% and 80%–10%–10%, respectively. Based on these performance comparisons, the model setting #15 is chosen for the WTI crude oil price time series. For assessments of performance sensitivities for price series of the other three energy commodities presented in Fig. 5, the way to interpret the results are similar to that for the price series of the WTI crude oil. And these results in Fig. 5 support the choices of the model configuration #1 for Brent crude oil, the model configuration #33 for New York Harbor No. 2 heating oil, and the model configuration #21 for Henry Hub natural gas. The training, validation, and testing phases have respective RRMSEs of 1.96%, 1.96%, and 1.87% based on the model configuration #15, and the overall RRMSE for WTI crude oil is 1.95%. RRMSEs for training, validation, and testing based on chosen parameters for the four commodities are shown in Fig. 6. For training, validation, and testing, the chosen setup yields RRMSEs of 1.81%, 1.80%, and 1.78% for the Brent crude oil, 9.75%, 8.76%, and 9.10% for the New York Harbor No. 2 heating oil, and 21.76%, 14.41%, and 16.97% for the Henry Hub natural gas. The overall RRMSEs based on the chosen parameters are 1.80%, 9.51%, and 20.35%, respectively, for Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas. As RRMSEs for the testing phase are 1.87%, 1.78%, 9.10%, and 16.97% for prices of the WTI crude oil, Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas, respectively, prediction accuracy of our constructed models could be rated as excellent for prices of the first three energy commodities and good for prices of Henry Hub natural gas, according to previous studies [137–140]. It is worth noting that as compared to prices of other three energy commodities, those of Henry Hub natural gas reveal relatively larger RRMSEs. This could be partly due to the relatively smaller amount of price data for model training for Henry Hub natural gas, recalling that the numbers of observations are 2521 (daily), 2537 (daily), and 424 (monthly) for WTI crude oil, Brent crude oil, and New York Harbor No. 2 heating oil, respectively, while the number of observations is 297 (monthly) for Henry Hub natural gas. The relatively larger RRMSE should also be related to quite some large jumps in prices during the training phase for Henry Hub natural gas, which could affect performance of the constructed model. Fig. 5 shows that, with the exception of the New York Harbor No. 2 heating oil testing phase, the LM algorithm often yields lower RRMSEs than the SCG method. This can be specifically seen in the performance comparison between model settings #1 and #2 for Brent crude oil, between model settings #15 and #16 for WTI crude oil, between model settings #33 and #34 for New York Harbor No. 2 heating oil, and between model settings #21 and #22 for Henry Hub natural gas. When compared to the SCG method, the LM algorithm achieves superior accuracy for neural networks with two hidden layers and a multi-layer perceptron structure. This is consistent with other research findings [141], which demonstrate that on a basic multi-layer

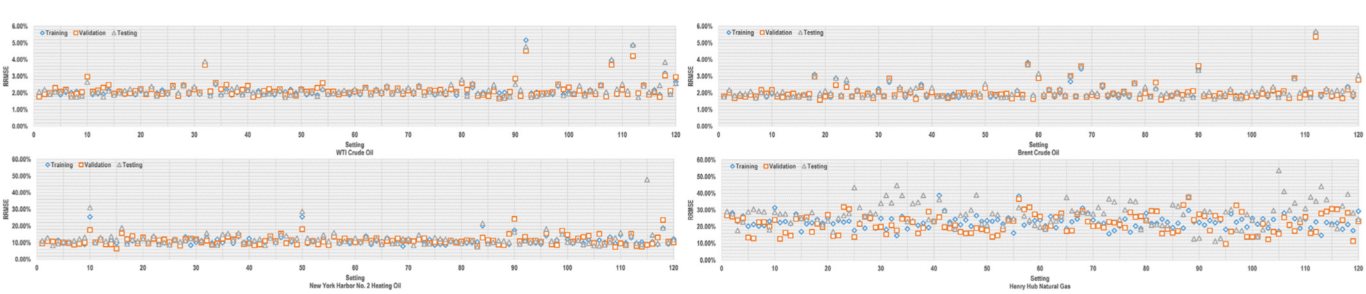


Fig. 4. RRMSEs across all model settings for daily price time series of the WTI crude oil and Brent crude oil and monthly price time series of the New York Harbor No. 2 heating oil and Henry Hub natural gas.

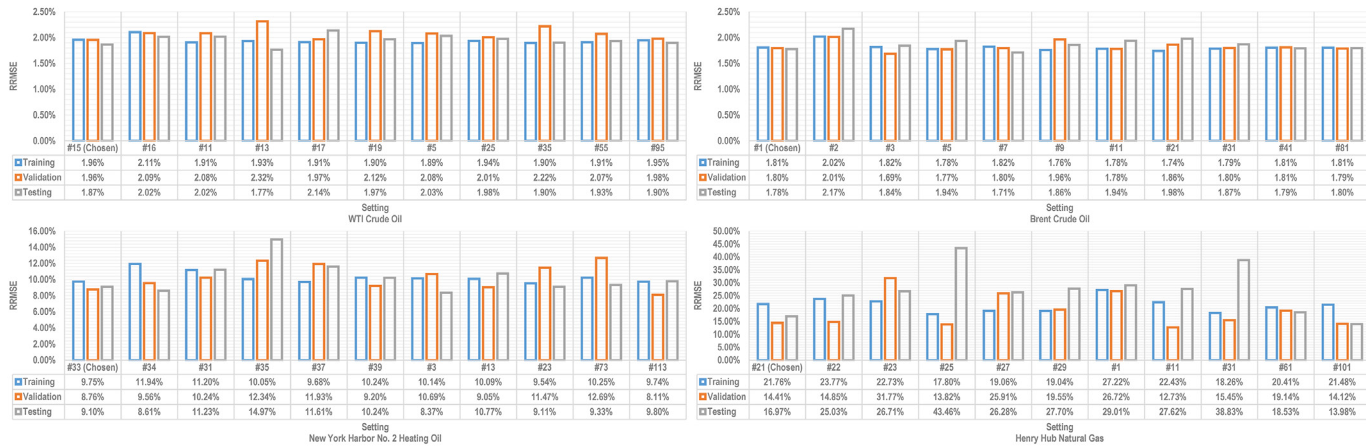


Fig. 5. Sensitivities of model performance measure by the RRMSE to different model configurations for daily price time series of the WTI crude oil and Brent crude oil and monthly price time series of the New York Harbor No. 2 heating oil and Henry Hub natural gas.

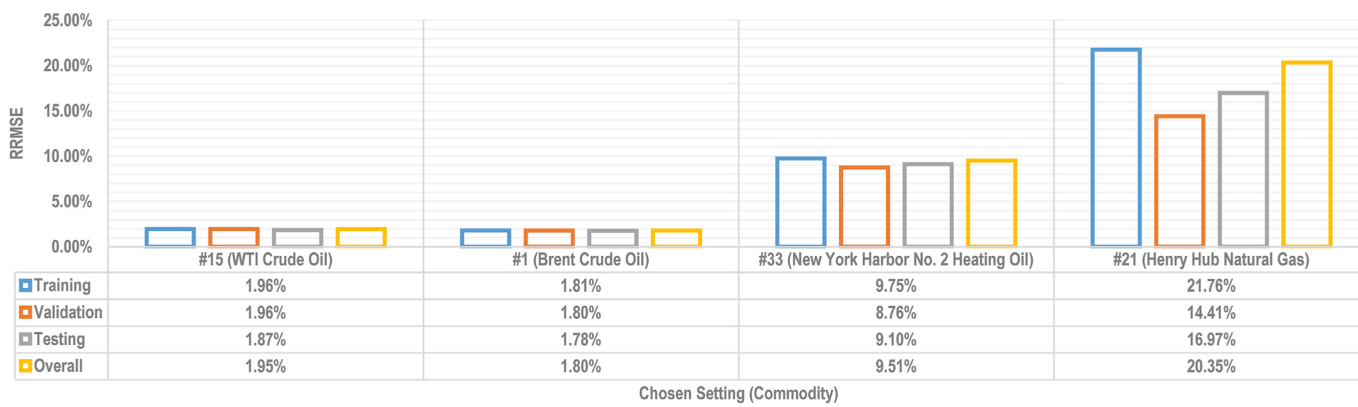


Fig. 6. Chosen model configurations and model performance for daily price time series of the WTI crude oil and Brent crude oil and monthly price time series of the New York Harbor No. 2 heating oil and Henry Hub natural gas.

perceptron structure with two hidden layers, the LM algorithm performed better in terms of accuracy (as indicated by the mean squared error and average training accuracy) while the SCG algorithm performed better in terms of speed (as indicated by the average training iteration). Detailed training time based upon the selected model configurations for the four energy commodities are reported in Table 4 according to model execution on the MATLAB platform with the Intel(R) Core(TM) i7-9700 CPU @ 3.00 GHz and 32 GB RAM, where it can be seen that the SCG algorithm is quicker than the LM algorithm for our case. Overall RRMSEs for the four commodities show that performance variances based on various ratios to segment price time series are quite minimal, indicating that overall performance is resilient against these data segmentation ratios employed.

For each of the four commodities, we show plots of the detailed forecasted results based on selected model settings in Fig. 7. The most left three subfigures on the top panel show the results for the WTI crude oil across the training phase, validation phase, and testing phase, the most right three subfigures on the top panel show the results for the Brent crude oil, the most left three subfigures on the bottom panel show the results for the New York Harbor No. 2 heating oil, and the most right three subfigures on the bottom panel show the results for the Henry Hub natural gas. When observed prices for Henry Hub natural gas leap to high levels during the training period, there are typically several rather big forecasting errors. All things considered, the chosen model parameters for the four commodities' price series produce accurate forecast performance outcomes that are consistent across various stages. In Fig. 7, the R^2 values of the linear fit regressions across subfigures are all more than 0.91. Moreover, the chosen model parameters do not result in the problem of consistent overprediction or underprediction throughout the phases and commodities, as shown by Fig. 7. Auto-correlations of errors have been analyzed for up to 20 lags in order to evaluate the suitability of the chosen model parameters. The findings, which are not presented here for brevity, can be obtained upon request. In general, the results do not fall outside of the 95% confidence bounds.

Table 4
Model training speed based upon the LM and SCG algorithms.

Energy price	Training time (in Second)	
	LM algorithm	SCG algorithm
WTI crude oil	0.877928	0.827383
Brent crude oil	0.509306	0.469533
New York Harbor No. 2 heating oil	0.262205	0.231109
Henry Hub natural gas	0.259032	0.226175

The literature has a wealth of information about the occurrences of nonlinearities in higher moments in financial and economic time series [142,143]. Here, we apply the BDS test [144] to the monthly price time series of Henry Hub natural gas and New York Harbor No. 2 heating oil as well as the daily price time series of WTI and Brent crude oil. Based on various testing scenarios, we find that the related $p-$ values are all almost zero. Neural network models may be used to simulate nonlinear aspects in the four commodities' price series in this particular scenario [81,120]. Other machine learning techniques might be taken into account while modeling nonlinearities. Using combinations of many

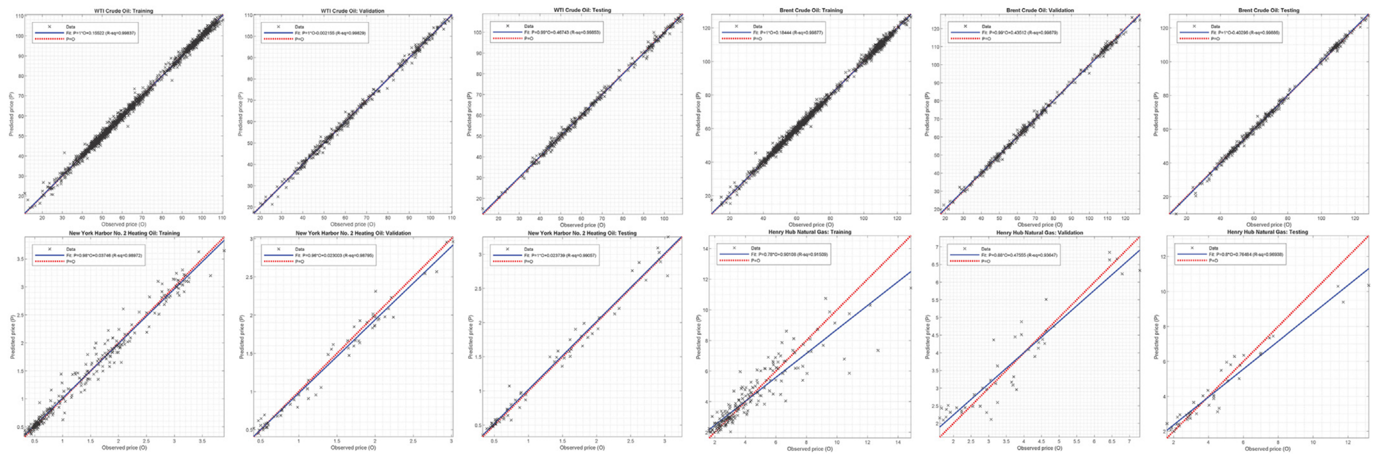


Fig. 7. Visualization of forecast results based upon chosen model configurations for daily price time series of the WTI crude oil and Brent crude oil and monthly price time series of the New York Harbor No. 2 heating oil and Henry Hub natural gas.

nonlinear functions rather than a single nonlinear function to approximate the underlying price time series is one benefit of neural network models [112,113,115]. Our investigation shows the potential of neural network models for predicting the prices of WTI crude oil, Brent crude oil, New York Harbor No. 2 heating oil, and Henry Hub natural gas. The prediction results obtained here are quite accurate and steady.

6. Conclusion

Making price projections for various energy commodities has always been a crucial duty for a wide range of energy market participants. In this work, we conduct the forecast exercise by concentrating on monthly price data for New York Harbor No. 2 heating oil during 06/1986 – 09/2021 and Henry Hub natural gas during 01/1997 – 09/2021. We also focus on daily price data for WTI crude oil during 09/26/2011 – 09/24/2021 and Brent crude oil during 09/26/2011 – 09/20/2021. In order to address these specific prediction challenges, we utilize the non-linear auto-regressive neural network model, taking into account various model variables such as training algorithms, hidden neurons, delays, and data segmentation. Based on the investigation, rather straightforward models are built that yield quite accurate and reliable performance. More precisely, the price series is divided into training, validation, and testing phases and trained using the Levenberg-Marquardt technique [125,126], which is adopted to build the models in the ratio of 70%–15%–15%. The WTI crude oil model has four delays and three hidden neurons; the Brent crude oil model has two delays and two hidden neurons; the New York Harbor No. 2 heating oil model has three delays and eight hidden neurons; and the Henry Hub natural gas model has two delays and five hidden neurons. The models generate relative root mean square errors of 1.96%/1.81%/9.75%/21.76%, 1.96%/1.80%/8.76%/14.41%, and 1.87%/1.78%/9.10%/16.97% for model training, validation, and testing, respectively, and an overall relative root mean square error of 1.95%/1.80%/9.51%/20.35% for the overall sample for WTI crude oil/Brent crude oil/New York Harbor No. 2 heating oil/Henry Hub natural gas. The outcomes of this projection might be used in technical analysis or integrated with other fundamental forecasts for policy analysis. This prediction framework should be fairly straightforward, which is something that many market participants and policy makers will find important to take into account. A forecast framework like this may be used for pertinent forecast issues involving several additional commodity price series from other economic sectors. There could be many different factors affecting energy prices, such as the international political and economic situation, market supply and demand relations, trade policy, and energy consumption status. The present work concentrates on constructing price forecast models based upon lagged prices. It should be a worthwhile avenue for future studies to incorporate these potentially useful exogenous factors when building energy price forecast models. As there could be possible coupling relationships among price series of different energy commodities, which could have useful implications for constructing price forecast models, another important research direction for future work would be studying such relationships.

CRediT authorship contribution statement

Bingzi Jin: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiaojie Xu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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