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China mainland new energy index price forecasting with the neural network

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ABSTRACT

For policymakers and investors, forecasting prices of energy indices has always been an important task. The present work focuses on the Chinese market and explores the daily price forecasting problem for the new energy index in the mainland during the period spanning January 4, 2016 – December 31, 2020. Our analysis is facilitated through the nonlinear autoregressive neural network model and one hundred and twenty model settings are tested in the fields of the algorithm for training the model, the number of hidden neurons utilized, the number of delays utilized, and the ratio utilized for segmenting the price series into different phases. Analysis here leads to the construction of a rather simple model based upon four delays and two hidden neurons with the Levenberg-Marquardt algorithm for training, which generates accurate and stable forecast results, with relative root mean square errors below 1.80% and mean absolute percentage errors below 1.30% across training, validation, and testing phases and for the overall sample. This constructed model also leads to statistically significantly better forecasting performance than a linear autoregressive model at the 1% significance level based upon the modified Diebold-Mariano test. The model built could be used as part of policy analysis for policymakers and decision making for investors. The forecasting results might also benefit design of similar energy indices by offering reference information in terms of price paths projected through the model.

1. Introduction

For policymakers and investors, forecasting prices of energy indices has always been an important task. As energy commodities naturally are considered as having strategic values to different countries and regions, forecasting their prices could play a significant role in planning for the future and uncertainties. Nearly all types of energy market participants would require price forecast information as part of decision making. For example, to energy plants, forecast information provides helpful insights into the setup of future sales prices. To trading partners, forecast information offers necessary details for arriving at contractual requirements. To traders and speculators, forecast information sheds light on possible opportunities for locking in profits from the spot or futures market. To risk managers, forecast information is deemed as an essential component of building risk monitoring strategies [1]. Because volatilities of energy commodity prices are generally irregular and many times large, their prices usually have immense influences on business outcomes and thus on welfare distributions ultimately. Therefore, one probably does not require too much motivation in considering significance of energy commodity price forecasting.

For the purpose of constructing accurate and stable price forecasts for different types of commodities, great efforts have been seen in earlier studies that adopt econometric models [2–56]. The ARIMA model [2,3,6,8,10,12,41,43,46,47,49,52,53], VAR model [8,10,14,16,18,20–24,26,27], and VECM model [14,21,22,29,31,32,57] have been found to offer useful forecast information under many different circumstances. The ARIMA model utilizes predictive information from past observations of the target to be forecasted and is univariate in nature. The VAR model augments predictive information utilized by the ARIMA model by incorporating economic relationships among different variables [58]. The VECM model, as compared to the VAR model, explicitly incorporates long-run relationships through the concept of cointegration among economic variables [59–61], making it particularly suitable for long-term forecasts [62].

With advancements in science, computational resources have become more affordable as compared to the previous decade. Correspondingly, forecasting research in the area of economics and finance has witnessed increasing interest in exploring different types of machine learning models [43,47,50,53,56,63–90]. These studies undoubtedly include price forecasts for energy markets. The neural network model [43,47,50,53,56,63,65,67,69,71,73,77,78,80–86,88–93], deep learning technique [69], support vector regression model [75,87,89], and boosting method [75] have been found to offer useful forecasts in this regard. For example, it was found that the neural network, combined

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with wavelet transformations of data, could be used to construct effective price forecasts for the Pennsylvania-New Jersey-Maryland electricity (PJM) market [63,90], as well as electricity demand and gas price forecasts for UK energy markets [50]. Similar evidence of potential of combining the neural network and wavelet transformations was reported for Indian Electricity Exchange [71] and US Energy Information Administration [80]. Another study proposed the combination of the ARIMA, radial basis function neural network, and wavelet transformations of data for electricity price forecasting for the Spanish market [47]. Also for the PJM market, a deep learning model based upon the stacked auto-encoder [69] and a combinatorial neural network model based upon stochastic searching [73] were found helpful in improving price forecasting accuracy. Switching to electricity price forecasting for the Nord Pool Scandinavian power market, the usefulness of a seasonal auto-regressive feedforward neural network was illustrated [65]. For marginal electricity price forecasting of the deregulated Victorian power system, a three-layered back-propagation neural network was determined to be a valuable tool [77]. For the same market, the neural network was found to have potential for producing accurate forecasts for both prices and loads [85]. The three-layer back-propagation neural network was also found to be promising for forecasts of market clearing prices and quantities for the California day-ahead energy market [82]. And the multi-layer perceptron neural network was found to outperform ARIMA models in terms of forecasting accuracy for electricity prices in the Spanish energy market [43]. When forecasting price volatilities of iron ore, the neural network trained via the chaotic grasshopper optimization algorithm was found to be promising for generating good accuracy [84]. Similarly, the neural network, combined with generalized auto-regressive conditional heteroskedasticity models, is found to be useful for forecasting price log-returns for the Chinese energy index in Shanghai Stock Exchange [56]. For electricity price forecasting for Indian Energy Exchange, the neural network was applied to data constructed using the similar-day approach and led to stable forecasts [67]. Another study for Indian Energy Exchange put forward the use of the long short-term memory neural network based upon the particle swarm optimization algorithm and found it accurate as well for forecasting market clearing prices [88]. For New South Wales, electricity price forecasting was explored via the support vector regression, boosting, and shrinkage methods, among which the least absolute shrinkage and selection operator regression and XGBoost were found optimal in terms of accuracy [75]. The good potential of the support vector regression for forecasting electricity prices was reported for the Spanish, New York, and New England markets [87]. For financialized energy commodity prices, it was found that the neural network, together with clustering analysis, could lead to accurate and stable spot electricity price forecasts, which offer helpful references for decision making in energy trading [78]. Similarly, the usefulness of the neural network with the single output node structure was demonstrated for forecasts of electricity prices for European Energy Exchange in Leipzig, which beats auto-regressive error models [81], and for forecasts of electricity prices for Mexico [83]. Another research focused on price forecasting of renewable energy company stocks in the US and China and suggested the use of a hybrid model constituted of the long-short term memory neural network, fractal dimension analysis, and the fruit fly algorithm, which outperforms the support vector regression [89]. Focusing on the Chinese energy market, a carbon price forecasting model was developed by combining multiple data decomposition techniques and extreme learning machines, which leads to good accuracy [94]. Another recent work proposed using the random forest and long short-term memory neural network for improving carbon price forecasting for Hubei and Guangdong carbon markets in China by exploring textual online news as sources of climate-related variables [95]. In forecasting financial prices of China Petroleum & Chemical Corp. and PetroChina Co. Ltd., the discrete wavelet transformation and stochastic recurrent wavelet neural network were combined to arrive at improved accuracy [96]. The neural network was also integrated with Facebook Prophet (Fb–P) algorithm for generating price forecasts of lithium mineral resources in China [97]. In addition to price forecasting, previous research suggested that the genetic algorithm based neural network could effectively forecast energy consumption in China [98]. Another recent study found that the adaptive differential evolution algorithm based back-propagation neural network outperforms many other models in forecasting the total energy consumption in China [99]. Based upon reviews of these previous studies here, the neural network model stands out to be the most popular machine learning approach to address price forecasting issues for different energy markets. The neural network model could model noised and chaotic price series under many different circumstances [100–105], stemming from the model's self-learning capabilities [106–108] and design for capturing nonlinear characteristics inhabiting in time series data [109–111].

From the data handling perspective, functional data analysis techniques applied on time series data have been found beneficial to forecasting exercises. For example, Shah, Iftikhar and Ali [112] applied a components estimation technique that decomposes time-series data into deterministic and stochastic components for the purpose of forecasting medium-term electricity consumption in Pakistan. Similarly, Shah, Bibi, Ali, Wang and Yue [113] employed the components estimation technique for the purpose of making one-day-ahead forecasts of electricity prices for the Italian electricity market. Shah, Iftikhar, Ali and Wang [114] demonstrated the usefulness of the components estimation technique for the purpose of forecasting electricity demand in the short run for the Nordic electricity market. Allen [115] explored the potential of functional data analysis for studying seasonalities in time-series data. Also focusing on the Italian electricity market, Jan, Shah and Ali [116] proposed using a functional forecasting approach, which integrates the functional final prediction error with a functional auto-regressive model, for the purpose of forecasting electricity prices in the short run. Elías, Jiménez and Shang [117] presented two nonparametric approaches for the purpose of forecasting functional time series and illustrated the usefulness of their methods based upon time-series data of electricity demand and NOx emissions. Similarly, Zou, Su and Chen [118] showed that functional versions of nonparametric models could successfully forecast the container throughput of the Shanghai port for the purpose of studying carbon emissions. The potential of functional time-series methods has also been found by Beyaztas and Shang [119] when conducting multi-step-ahead age-specific mortality rate forecasting. Klaar, Stefenon, Seman, Mariani and Coelho [120] investigated the time-series seasonal decomposition technique and different ensemble models, including the AdaBoost, bagging, gradient boosting, and random forest ensemble learning, that are optimized through the tree-structured Parzen estimator for the purpose of energy price forecasts in Latin America, particularly in Mexico, and arrived at high forecasting accuracy. For the case of Italian electricity spot prices, Stefenon, Seman, Mariani and Coelho [121] suggested that the combination of the seasonal and trend decomposition technique and the Facebook Prophet method could help improve forecasting accuracy. Ribeiro, Silva, Ribeiro, Mariani and Coelho [122] developed a cooperative ensemble learning model, which integrates different signal decomposition approaches, machine learning models, and hyperparameter optimizations based upon metaheuristics, for the problem of electric load forecasting in the short run and they found that the model outperforms more than 70% of other state-of-art models in terms of forecasting accuracy.

The present work focuses on the Chinese market and explores the daily price forecasting problem for the new energy index in the mainland during the period spanning January 4, 2016 – December 31, 2020. The index was constituted of four new energy stocks before December 12, 2016. On December 12, 2016, one new energy stock was added to the index. On June 12, 2017, another new energy stock was added to the index. On December 11, 2017, two new energy stocks were added to the index. On June 11, 2018, one new energy stock was added to the index. On December 17, 2018, two new energy stocks were added to the index. On June 17, 2019, one new energy stock was added to the index. On

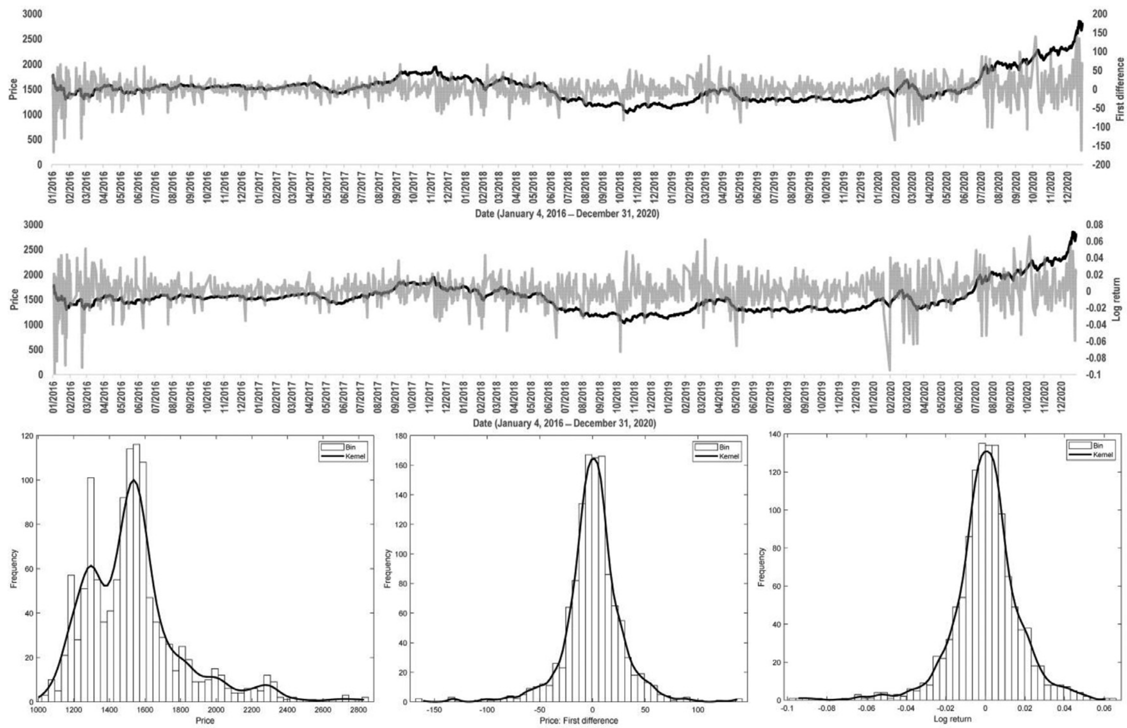


Fig. 1. Top panel: Daily closing prices (black line) and their first differences (grey line) of the China mainland new energy index; Middle panel: Daily closing prices (black line) and their log returns (grey line); Bottom panel: Histograms with fifty bins and kernel estimates of the prices, their first differences, and their log returns.

December 16, 2019, two new energy stocks were added to the index. On June 15, 2020, three new energy stocks were added to the index. The annual RMB volume of the index increases from 3.14 trillion in 2016 to 7.11 trillion in 2020. And the annual trading volume of the index increases from 0.214 trillion in 2016 to 0.448 trillion in 2020. The index is designed to reflect developments and general trends of the new energy sector in China and corresponds to the nation's strategic plan to continuously explore new energy for sustainable economic growth. While our sample ends in 2020, there have been more new energy stocks added to the index since the year, which corresponds to the initiative of cleaner energy use. Although there exist different opinions about the trends of individual new energy stocks, it is generally acknowledged that the index will continue to expand in the near future. Our analysis is facilitated through the nonlinear autoregressive neural network model, which has been found in the literature to have great potential to model noised, chaotic, and volatile price series such as the new energy index under consideration [100–111], and one hundred and twenty model settings are tested in the fields of the algorithm for training the model, the number of hidden neurons utilized, the number of delays utilized, and the ratio utilized for segmenting the price series into different phases to determine the setting that best adapts to characteristics of the underlying new energy index. Analysis here leads to the construction of a rather simple model that generates accurate and stable forecast results, with relative root mean square errors below 1.80% across training, validation, and testing phases. The model built could be used as part of policy analysis for policymakers and decision making for investors.

2. Data

Data analyzed here, sourced from Wind Information Co., Ltd.[1], are daily closing prices (RMB/share) of the China mainland new energy index. The sample spans the period of January 4, 2016 – December 31, 2020. On the top panel of Fig. 1, we show the price series and its first-difference series. On the middle panel of Fig. 1, we show the price series and its log-return series. On the bottom panel of Fig. 1, we show fifty-bin histograms and kernel estimates of the price series and its first-difference and log-return series. In Table 1, we report summary statistics of the price series and its first-difference and log-return series, including the minimum, mean, median, maximum, standard deviation, skewness, and kurtosis. It could be seen from Table 1 that the price series is right-skewed while its first-difference and log-return series are left-skewed. Meanwhile, the price series and its first-difference and log-return series are all leptokurtic.

A vast number of studies [100,102,105,106,108,123,124] have reported existence of nonlinearities in higher moments of economic time-series data. Thus, we utilize the BDS test [125] for the purpose of assessing possible nonlinearities inhabiting the daily closing price of the China mainland new energy index. We find that $p-$values of the test corresponding to different testing scenarios are all nearly zero, thus confirming nonlinear patterns in the price series. For this situation, the neural network model would be suitable for modeling underlying nonlinear features. As compared to some other nonlinear modeling techniques that rely on one particular nonlinear function, the neural network model utilizes combinations of many different nonlinear functions, making it a good choice for approximating the price series with nonlinear characteristics.

3. Method

The nonlinear autoregressive neural network model could be written as

$$y_t = f(y_{t-1}, \dots, y_{t-d}). \tag{1}$$

Here, y is utilized to denote the price series to be forecasted, t is utilized to denote time, d is utilized to denote the number of delays, and f is utilized to denote the function form of the model. The estimate of f could be written as

[1] https://www.wind.com.cn/

Table 1
Summary statistics of daily closing prices of the China mainland new energy index.

Series	Minimum	Mean	Median	Maximum	Standard deviation	Skewness	Kurtosis
Price	1028.8900	1534.8551	1511.0550	2852.8800	275.6992	1.3744	5.9587
First difference	166.8100	0.8583	0.8100	139.8300	27.5215	0.4782	9.1983
Log return	0.0983	0.0004	0.0006	0.0656	0.0171	0.7910	7.7325

$$y_t = \alpha_0 + \sum_{j=1}^{k} \alpha_j \phi\left(\sum_{i=1}^{d} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t. \tag{2}$$

Here, k is utilized to denote the number of hidden layers with the transfer function denoted as ϕ, β_{ij} is utilized to denote the parameter corresponding to the weight of the connection between the input unit denoted as i and the hidden unit denoted as j, α_j is utilized to denote the weight of the connection between the hidden unit denoted as j and the output unit, β_{0j} and α_0 are utilized to denote the constants corresponding, respectively, to the hidden unit denoted as j and the output unit, and ε is utilized to denote the error term. The current work will focus on conducting one-day ahead price forecasts. The neural network model with the structure of the two-layer feed-forward is adopted here. The sigmoid transfer function, whose function form is denoted as

$$\phi(z) = \frac{1}{1+e^{-z}}, \tag{3}$$

is used for the hidden layer and the linear transfer function is used for the output layer[2].

The final neural network model selected here utilizes four delays and two hidden neurons. It is trained through the Levenberg-Marquardt (LM) algorithm [126,127] with 70%–15%–15% as the ratio for segmenting the price series into training–validation–testing phases. The LM algorithm is rather efficient in the sense that it does not compute the Hessian matrix denoted as H but approximates the second-order training speed [128]. In this algorithm, using a system whose weights are denoted as w_1 and w_2 as an example, the approximation

$$H = J^T J \tag{4}$$

will be made, where

$$J = \begin{bmatrix} \frac{\partial E}{\partial w_1} & \frac{\partial E}{\partial w_2} \end{bmatrix} \tag{5}$$

for the non-linear function $E(\cdot)$ that contains the information of the sum square error whose

$$H = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} \end{bmatrix}. \tag{6}$$

The gradient could be written as

$$g = J^T e, \tag{7}$$

where e is utilized to denote the error vector. For making updates to weights and biases, the rule written as

$$w_{k+1} = w_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{8}$$

is utilized, where w is utilized to denote the weight vector, k is utilized to denote the index of the training iteration, I is utilized to denote the identity matrix, and μ is utilized to denote the positive combination coefficient. The LM algorithm is similar to the Newton method for $\mu = 0$ and is gradient descent with small step sizes for large μ values. With successful iterations, the value of μ would decrease because there would be reduced requirements for fast gradient descent. In the meanwhile, the LM algorithm could avoid several limitations in steepest-descent algorithms, including its capability of handing slow convergence [129].

For training a neural network model, there are many algorithms that one could explore. Here, the scaled conjugate gradient (SCG) algorithm [130] is investigated as well, in addition to the LM algorithm aforementioned. For backpropagation algorithms, adjustments of weights are generally performed in the steepest descent. This is related to the benefit that the performance function would rapidly decrease in that direction. The potential issue, however, is that this does not guarantee the fastest convergence. Therefore, for conjugate gradient algorithms, searches are carried out along conjugate directions for the purpose of deciding step sizes for reducing the performance function during the iterative process. In the meanwhile, the speed of convergence is also usually faster than the steepest descent. To further increase the speed, the SCG algorithm gets rid of line searches that are usually performed in conjugate gradient algorithms. Both the SCG and LM algorithms have been successfully applied for many different research realms [131–138]. The literature [139–143] has also reported particular comparative analysis of these two algorithms.

During the process of arriving at our final neural network model, different settings in addition to different algorithms are tested in the areas of the number of delays utilized, the number of hidden neurons utilized, and the ratio utilized for segmenting the price series into different phases for model training, validation, and testing. For the number of delays, we consider two, three, four, five, and six. For the number of hidden neurons, we consider two, three, five, and ten. And for the ratio for segmenting the price series, we consider 60%–20%–20%, 70%–15%–15%, and 80%–10%–10% for training–validation–testing. As the new energy price index time series considered here has 1212 observations, the ratio of 60%–20%–20% for training–validation–testing corresponds to 728 observations for training and 242 observations for both validation and testing. Similarly, the ratio of 70%–15%–15% for training–validation–testing corresponds to 848 observations for training and 182 observations for both validation and testing. And the ratio of 80%–10%–10% for training–validation–testing corresponds to 970 observations for training and 121 observations for both validation and testing. To terminate the process of training the model, we consider the magnitude of the gradient as well as the number of validation checks. When training yields the lowest possible performance, the gradient will become quite modest. If the gradient's magnitude is less than 10^{-5}, training will end. The number of validation checks is equal to the number of subsequent rounds where the performance of validation fails to decrease. The number of validation checks we utilize is six, and once it is met, training will end. Additionally, we set a maximum of 1000 training iterations (or epochs), after which training would come to an end. We use 0.001 as the initial combination coefficient (abbreviated as μ) for the LM algorithm, 0.1 as the decrease factor, 10 as the increase factor, and 10^{10} as the maximum value of μ. We employ 5×10^{-5} as the weight change determinant linked to second derivative approximations, 0.005 as the Marquardt adjustment parameter, and 5×10^{-7} as the parameter to control the indefiniteness of the Hessian for the SCG algorithm. We show all considered neural network model settings in Table 2 and our final selected setting is #5. Analysis of this work is conducted through MATLAB and functions as follows are used: *tonndata, narnet, preparets, train*, and *perform*. The time consumed to execute our final selected model setting #5 is 2.507100 seconds with the Intel(R) Core(TM) i7-9700 central processing unit.

[2] Delays are utilized for feeding the output back to the neural network. For model training efficiency, the open loop form is utilized and the true, not estimated, output is used. This form could ensure that the input to the neural network is more accurate.

Table 2
Explored model settings for daily closing prices of the China mainland new energy index .

	Model setting	Setting index
Algorithm	Levenberg-Marquardt (LM)	1+2i (i=0,1,...,59)
	Scaled conjugate gradient (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)
	10	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

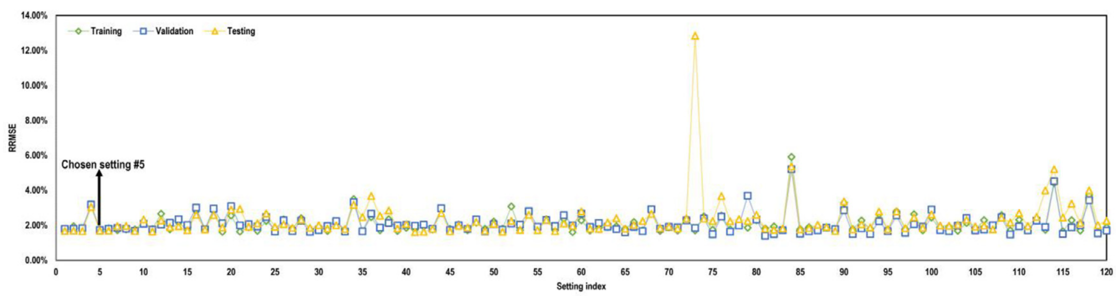


Fig. 2. RRMSEs across all model settings for daily closing prices of the China mainland new energy index. The horizontal axis, “setting index,” in this plot corresponds to the “setting index” column in Table 2. For example, when “setting index” is 5 in this plot, we can refer to Table 2 and find that the corresponding model setting is based upon the LM algorithm ($i = 2$ in Table 2), 4 delays ($j = 0$ in Table 2), 2 hidden neurons ($k = 0$ in Table 2), and the data splitting ratio of 70%, 15%, and 15% for the training, validation, and testing phases. For each setting index on the horizontal axis, the vertical axis shows the RRMSEs associated with the training, validation, and testing phases using the diamond, square, and triangular shapes, respectively.

4. Result

We conduct evaluations of all model settings reported in Table 2 for daily closing prices of the China mainland new energy index. For this analysis, we utilize the relative root mean square error, denoted as RRMSE, as the metric for assessing forecast accuracy. The formula of the RRMSE is

$$\mathrm{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^{obs} - y_i^{for})^2}}{\frac{1}{n}\sum_{i=1}^{n} y_i^{obs}}, \tag{9}$$

where n stands for the number of observations for performance assessments, y^{obs} stands for the observed value of the target, and y^{for} stands for the forecasted value of the target. The RRMSE allows for comparisons of forecast results across models and targets [144–147]. Previous studies [144–147] suggest considering model accuracy excellent for RRMSE<10%, good for 10%<RRMSE<20%, fair for 20%<RRMSE<30%, and poor for RRMSE≥30%. Fig. 2 presents results of RRMSEs across model training, validation, and testing phases generated from each neural network model setting shown in Table 2. Specifically, for each setting index on the horizontal axis in Fig. 2, the vertical axis shows the RRMSEs associated with the training, validation, and testing phases using the diamond, square, and triangular shapes, respectively. When we make the decision on the final model setting to proceed for generating detailed forecasts, we take into account the need of building forecasts that are both accurate and stable across different phases. As a result, we select the model setting #5. This model setting utilizes four delays and two hidden neurons. Fig. 3 shows the block diagram of the selected model setting #5. And the corresponding algorithm used for model training is the LM algorithm. Meanwhile, the model is estimated based upon the ratio of 70%–15%–15% for segmenting the price series into training–validation–testing. We utilize the dark arrow to mark the selected model setting #5 in Fig. 2, from which we could see that its associated RRMSEs across the three phases are rather close to each other and are rather small. There does exist other model settings that produce a smaller RRMSE than the model setting #5 for a particular phase but larger RRMSEs for the other two phases, meaning that forecast stabilities are lowered. For example, the model setting #7 produces a smaller RRMSE than the model setting #5 for the training phase but larger RRMSEs for the validation and testing phases. With the selection of the model setting that balances forecast accuracy and forecast stabilities, the problem of overfitting or underfitting could be avoided.

Having the neural network model setting decided for the price series of the China mainland new energy index, the analysis turns to assessing sensitivities of forecast accuracy to different model settings. This analysis is facilitated by changing one setting field a time of the model setting #5 and comparing the resultant performance. Corresponding results of the analysis are present in Fig. 4, where the comparison between the model setting #5 and the model setting #6 is utilized for assessing the sensitivity of forecast accuracy to the algorithm utilized for model training because the only difference between these two model settings is that the model setting #5 is based upon the LM algorithm while the model setting #6 is based upon the SCG algorithm. Comparisons between the model setting #5 and model settings #1, #3, #7, and #9 are utilized for assessing sensitivities of forecast accuracy to the number of delays used because the only difference between the model setting #5 and these four alternative model settings is that different numbers of delays are used. Comparisons between the model setting #5 and model settings #15,

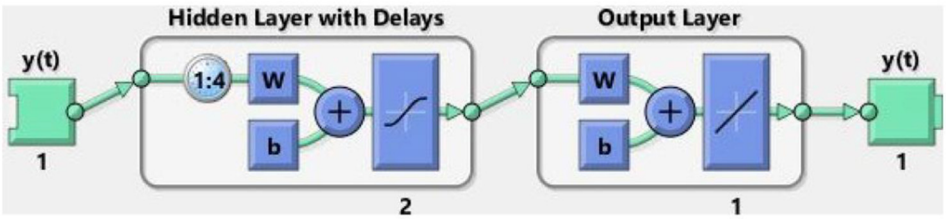
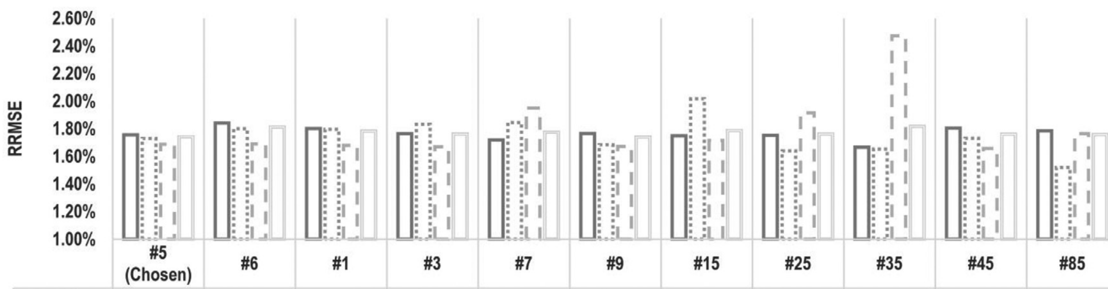


Fig. 3. The block diagram representing the two-layer feedforward neural network based upon the model setting #5 with 4 delays and 2 hidden neurons that is trained through the Levenberg-Marquardt (LM) algorithm[126,127]. The hidden layer is based upon the logistic sigmoid transfer function and the output layer is based upon the linear transfer function..



	#5 (Chosen)	#6	#1	#3	#7	#9	#15	#25	#35	#45	#85
Training	1.76%	1.84%	1.80%	1.76%	1.72%	1.77%	1.75%	1.75%	1.67%	1.80%	1.78%
Validation	1.73%	1.80%	1.80%	1.83%	1.84%	1.68%	2.02%	1.64%	1.65%	1.73%	1.52%
Testing	1.69%	1.69%	1.68%	1.67%	1.95%	1.67%	1.72%	1.91%	2.47%	1.66%	1.76%
Overall	1.74%	1.81%	1.78%	1.76%	1.77%	1.74%	1.79%	1.76%	1.82%	1.76%	1.76%

Setting index

Fig. 4. Sensitivities of model performance (the RRMSE) to different model settings for daily closing prices of the China mainland new energy index.

#25, and #35 are utilized for assessing sensitivities of forecast accuracy to the number of hidden neurons used because the only difference between the model setting #5 and these three alternative model settings is that different numbers of hidden neurons are used. Comparisons between the model setting #5 and model settings #45 and #85 are utilized for assessing sensitivities of forecast accuracy to the ratio used for segmenting the price series into different phases because the only difference between the model setting #5 and these two alternative model settings is that different ratios are used. These comparative analysis results provide support for our selection of the model setting #5. Based upon this model setting, RRMSEs generated are 1.76%, 1.73%, and 1.69%, respectively, corresponding to the training phase, validation phase, and testing phase, and the overall RRMSE generated is 1.74%. We also calculate model performance based upon the mean absolute percentage error (MAPE), whose formula is

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i^{obs} - y_i^{for}}{y_i^{obs}}\right|, \tag{10}$$

where n stands for the number of observations for performance assessments, y^{obs} stands for the observed value of the target, and y^{for} stands for the forecasted value of the target. Based upon the model setting #5, MAPEs are 1.17%, 1.24%, and 1.14%, respectively, corresponding to the training phase, validation phase, and testing phase, and the overall MAPE is 1.18%. From results in Fig. 4, we could see that the LM algorithm produces smaller RRMSEs than the SCG algorithm, as reflected through the comparison between the model setting #5 and the model setting #6. This result is consistent with the literature [148] that reports the faster speed of the SCG algorithm as compared to the LM algorithm at the cost of slightly reduced accuracy. Also from results in Fig. 4, we could see that overall accuracy is rather close across different ratios used for segmenting the price series, suggesting that overall model performance is robust, in general, against this modeling choice.

Based upon the selected model setting #5, we show forecast results in the top panel of Fig. 5, forecast errors in the middle panel of Fig. 5, and percentage forecast errors in the bottom panel of Fig. 5. These plots include results for the training, validation, and testing phases. From Fig. 5, we could see that the model setting #5 results in forecast results that are both accurate and stable across the three phases. There does not exist the issue of persistent overprediction or underprediction for any of the three phases. For several sporadic sub-periods when volatilities of prices are elevated, we could see that forecast errors become relatively larger. This is not surprising given the model design and the selected model setting still captures trends of prices during these sub-periods. We have also performed auto-correlation analysis of the errors generated by the model setting #5 (results are omitted for brevity but are available upon request) for assessing its adequacy. Particularly, the analysis has been conducted for up to twenty lags. We find that except for the eleventh lag, all auto-correlations are within the 95% confidence limits. And for this single slight breach, it falls within the 99% confidence limits. The model setting #5 is thus found to be adequate.

We have conducted benchmarking of the neural network model setting #5 against a linear autoregressive model, denoted as LAR, that utilizes the same number of delays and same data segmentation ratio as the model setting #5. Fig. 6 presents comparative analysis in terms of percentage forecast errors based upon the model setting #5 and the LAR model. It could be found from Fig. 6 that the model setting #5 outperforms the LAR model. We have also compared forecast results of these two different models based upon the modified Diebold-Mariano [149] test [150]. The test is based upon

$$d_t = \left(\text{error}_t^{M_1}\right)^2 - \left(\text{error}_t^{M_2}\right)^2, \tag{11}$$

where $\text{error}_t^{M_1}$ and $\text{error}_t^{M_2}$ are utilized to denote errors recorded for time t that are generated from models M_1 and M_2, respectively. Here, we can denote the LAR model as M_1 and the model setting #5 as M_2. The test statistic used for comparing model forecast accuracy is:

$$MDM = \left[\frac{T + 1 - 2h + T^{-1}h(h-1)}{T}\right]^{1/2}\left[T^{-1}\left(\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right)\right]^{-1/2}\bar{d}, \tag{12}$$

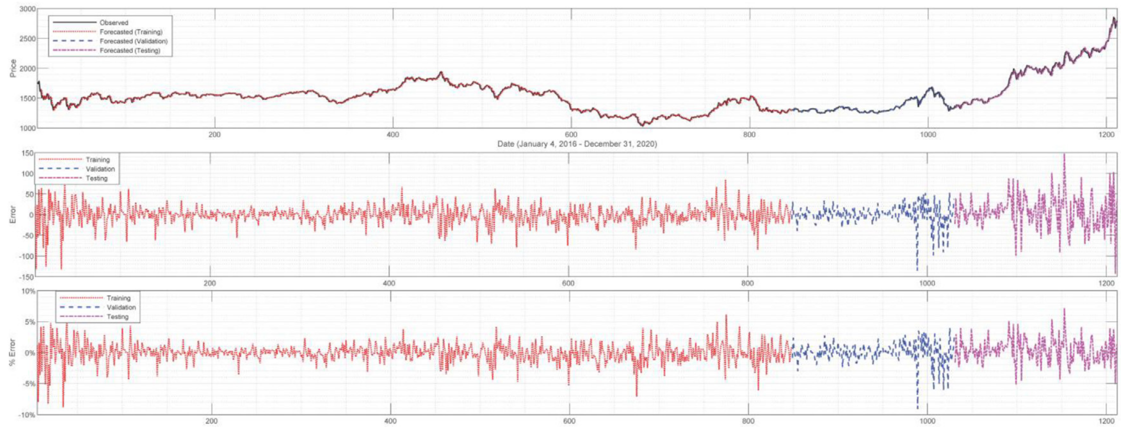


Fig. 5. Forecasts (top panel), forecast errors calculated as observations minus forecasts (middle panel), and percentage forecast errors (bottom panel) calculated as forecast errors divided by observations for daily closing prices of the China mainland new energy index.

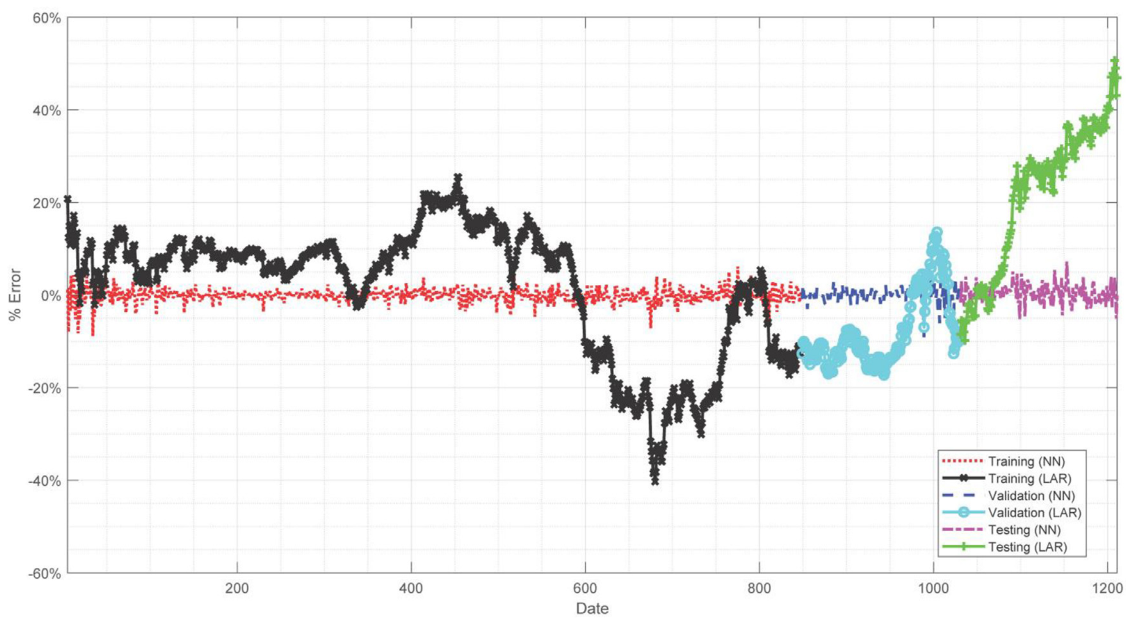


Fig. 6. Benchmarking of the setting #5 (NN) against the linear autoregressive (LAR) model: Comparisons of percentage forecast errors.

where T is used to denote the length of the sample for which the comparison is being conducted, h is used to denote the forecast horizon ($h = 1$ for our case), $\bar{d}$ is used to denote the sample mean of d_t,

$$\gamma_0 = T^{-1} \sum_{t=1}^{T} \left(d_t - \bar{d}\right)^2 \tag{13}$$

is used to denote the variance of d_t, and

$$\gamma_k = T^{-1} \sum_{t=k+1}^{T} \left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right) \tag{14}$$

is used to denote the kth auto-covariance of d_t for $k = 1, \ldots, h-1$ and $h \geq 2$. Under the null hypothesis of equal mean squared errors produced by two models under consideration, the MDM test would follow the t–distribution with $T - 1$ degrees of freedom. The p values of the MDM test are smaller than 0.001 across the training, validation, and testing phases, indicating that accuracy of the model setting #5 is statistically significantly better than that of the LAR model.

As the world and China are making efforts to transition to cleaner energy and achieve the goal of sustainable economic growth, the establishment of the new energy index carries great value as part of this global initiative. To have good understandings of the new energy index and its development, the corresponding price forecasting is an important exercise to policymakers as good forecasts could help guide policy design in right directions. However, this task could be difficult, especially considering that the new energy index is at its relatively early development phase, is continuously evolving, and is influenced by local and international economic and political factors, all of which could contribute to the volatile characteristic of the price time series. Under this circumstance, a model that is not overly complicated to policymakers but could effectively handle the potential irregular price series could be developed to benefit forecast users. Here, we pursue the forecasting exercise through the nonlinear auto-regressive neural network technique. Through our analysis, we construct a relatively simple model that generates accurate and stable forecasting results and this model is also demonstrated to show better performance as compared to a traditional linear auto-regressive model. While our work focuses on the Chinese market, the forecasting results might also benefit design of similar energy indices in different countries and regions by offering reference information in terms of price paths projected through the neural network model.

5. Conclusion

For policymakers and investors, forecasting prices of energy indices plays an important role in many decision making processes. The present work focuses on the Chinese market and explores the daily price forecasting problem for the new energy index in the mainland during the period spanning January 4, 2016 – December 31, 2020. Our analysis is facilitated through the nonlinear autoregressive neural network model and one hundred and twenty model settings are tested in the fields of the algorithm for training the model, the number of hidden neurons utilized, the number of delays utilized, and the ratio utilized for segmenting the price series into different phases. Analysis here leads to the construction of a rather simple model that generates accurate and stable forecast results, with relative root mean square errors below 1.80% across training, validation, and testing phases. The model built could be used as part of policy analysis for policymakers and decision making for investors. The forecasting framework utilized here is rather straightforward and has the potential to be extended to address price forecasting problems for other commodities from different business sectors. While the present work focuses on forecasts of commodity prices, forecasts of price returns and price fluctuations/directions are another important and interesting research direction to pursue, for which machine learning approaches have also revealed potential in the literature [151–155] and could be well worth the effort for future endeavors. A recent idea in time-series forecasting is the use of functional data analysis [156–158]. It is a worthwhile avenue to pursue for future studies.

Compliance with Ethical Standards

No funding received. No conflict of interest.

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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