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Commodity price forecasting via neural networks for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

Xiaojie Xu | **Yun Zhang**

North Carolina State University, Raleigh, NC, USA

Correspondence
Xiaojie Xu, North Carolina State University, Raleigh, NC 27695, US.
Email: xxu6@ncsu.edu

Summary

Agricultural commodity price forecasting represents a key concern for market participants. We explore the usefulness of neural network modeling for forecasting problems in datasets of daily prices over periods of greater than 50 years for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. By investigating different model settings across the algorithm, delay, hidden neuron, and data-splitting ratio, we arrive at models leading to a decent performance for each commodity, with the overall relative root mean square error ranging from 1.70% to 3.19%. These results have small advantages over no-change models due to particular price adjustments in the prices considered here. Our results can be used on a standalone basis or combined with fundamental forecasts in forming perspectives of commodity price trends and conducting policy analysis. Our empirical framework should not be difficult to implement, which is a critical consideration for many decision-makers and has the potential to be generalized for price forecasts of more commodities.

KEYWORDS
Agricultural commodity, Commodity price, Neural network machine learning, Price forecasting, Time series

1 | INTRODUCTION

Agricultural commodity price forecasting represents a key concern for market participants, such as producers, processors, brokers, and hedgers. It is important for producers in fixing sales prices ahead of production, processors and exporters in covering requirements, and speculators in generating profits. Due to high price volatilities (Timmermann, 2006), significant influences on decision-making, and hence on resource allocation and economic welfare, the importance of commodity price forecasting to the agricultural sector is evident. Previous research (Bessler et al., 2003; Xu, 2020; Yang et al., 2021) concentrates on a wide variety of econometric approaches, commercial services, and expert forecasts. Common econometric models for commodity price forecasting include the autoregressive moving average, vector autoregressive, and vector error correction models. Recently, machine learning techniques (Bayona-Oré et al., 2021), such as the neural network (Fang et al., 2020; Ribeiro & Oliveira, 2011), deep learning (Manogna & Mishra, 2021), extreme learning (Kouadio et al., 2018), genetic programming (Ali et al., 2018), support vector regression (Harris, 2017; Li, Chen, et al., 2020), K-nearest neighbor (Gómez et al., 2021), multivariate adaptive regression splines (Dias & Rocha, 2019), random forest (Gómez et al., 2021), decision tree (Harris, 2017), ensemble (Fang et al., 2020), and boosting methods (Gómez et al., 2021), have shown great potential for forecasting of prices and yields of coffee (Kouadio et al., 2018), corn (Xu & Zhang, 2021), cotton (Ali et al., 2018; Fang et al., 2020), oats (Harris, 2017), soybeans (Li et al., 2020; Ribeiro & dos Santos Coelho, 2020), soybean oil (Li, Chen, et al., 2020), sugar (Ribeiro & Oliveira, 2011), and wheat (Fang et al., 2020; Gómez et al., 2021). In particular, previous studies show that the neural network has great potential to forecast economic and financial time series, which tend to have certain nonlinearities (Wang & Yang, 2010; Yang et al., 2008). The literature also shows that the neural network can lead to high accuracy under many different forecasting settings (Wegener et al., 2016). This could benefit from the neural network's capability of self-learning for forecasting (Karasu et al., 2020) and capturing nonlinearities (Altan et al., 2021) often inhabiting economic and financial time series. One of the greatest advantages of the neural network over other nonlinear models for time series is that a class of multilayer neural networks could approximate a large class of functions well (Yang et al., 2010). We will focus on the neural network for forecasting prices of eight agricultural commodities in this study, including coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat.

There have been advancements in machine learning forecasting techniques in the economic and financial space in the literature. Zhang (1994) explores neural networks in searching for nonlinear relationships in high-frequency tick-by-tick bid prices for the Swiss franc to the US dollar exchange rate and building forecast models. They find, through a trading rule and under moderate transaction costs, that neural networks could lead to profit, which linear models could not achieve. Kohara et al. (1997) focus on daily stock price forecasts, and they find that using prior knowledge to select event knowledge and economic indicators for neural networks helps forecast performance. This approach is superior to methods based on linear models. Vojinovic et al. (2001) study the radial basis function neural network for daily \$US/\$NZ closing exchange rate forecasting and find that it leads to better performance than linear autoregressive models for both the exchange rate itself and its directional changes. Davis et al. (2001) explore different neural networks, including backpropagation, modular, radial basis functions, linear vector quantization, fuzzy ARTMAP, and genetic reinforcement learning, for directional forecasts of Canadian–US exchange rates and find that they beat the naive (no-change) model. Trinkle (2005) compares an adaptive network-based fuzzy inference system (ANFIS), a neural network, and an autoregressive moving average (ARMA) model for forecasting and trading of three publicly traded companies and finds that the ANFIS or neural network does not consistently outperform the ARMA. Quek et al. (2009) take the perspective of portfolio managers and focus on trading in the medium- and long-term. They propose the generic self-organizing fuzzy neural network (GenSoFNN) supplemented with reinforcement learning techniques for forecasting forthcoming inflection points as signals for balancing the portfolio. Leung et al. (2009) concentrate on trading of a financial-engineered (synthetic) derivative composed of options on foreign exchange futures. They put forward a hybrid neural network for guiding the trading and find that it leads to better results in terms of the profitability and market timing ability than econometric models. Dunis et al. (2013) compare trading simulations based on forecasts from an ARMA (12,12) model, a cointegration model, a multilayer perceptron neural network, a particle swarm optimization radial basis function neural network, and a genetic programming algorithm (GPA) for the Gold Miner Spread and find that the GPA model leads to the highest risk-adjusted returns. Fadlalla and Amani (2014) apply the multilayer perceptron neural network to forecast the Qatar Exchange index price and find that it outperforms ARMA models. They also find that the neural network is resilient to stock market volatilities. Parot et al. (2019) suggest the combination of the neural network model, vector autoregressive model, and vector error correction model for improving forecast accuracy from an individual model for EUR/USD exchange rate returns. R. L. Manogna and A. K. Mishra (2021) examine the price forecasting problem for the cotton seed, castor seed, rape mustard seed, soybean seed, and guar seed traded in National Commodity and Derivatives Exchange in India through deep-learning neural networks. They find that the long short-term memory neural network outperforms the time-delay neural network and ARMA model. Khedr et al. (2021) survey different machine learning techniques for cryptocurrency price forecasting, including the artificial neural network, deep learning, and reinforcement learning, among others.

Selection of the eight aforementioned commodities for analysis is generally due to their economic significance or great benefits to society. For example, coffee production is vital to the economy in Ethiopia, and about 15 million people are involved in the industry directly or indirectly (USDA, 2021a). Corn is the most widely produced feed grain in the United States, which accounts for greater than 95% of total production and use (USDA, 2021b). Cotton is one of the most important textile fibers across the globe, which averages approximately 25% of total global fiber use (USDA, 2021c). Oats are recognized as an important functional food for health (Behall & Hallfrisch, 2011). Processed soybeans are the world's greatest source of protein feed for animals and the second largest source of vegetable oil, which is soybean oil (USDA, 2021d). Sugar production is rising globally, with production increasing in Thailand, India, and the European Union, and its consumption is also predicted to rise to a new record, given the growth in markets in countries such as China and India (USDA, 2021e). Wheat, just behind corn and soybeans, ranks third among field crops in planted acreage, production, and gross farm receipts in the United States (USDA, 2021f).

To facilitate the analysis, we explore forecasting problems in datasets of daily prices over periods of greater than 50 years for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. We investigate different neural network model settings across the algorithm, delay, hidden neuron, and data-splitting ratio and arrive at models leading to accurate and stable performance for each commodity, with the overall relative root mean square error ranging from 1.70% to 3.19%. To the authors' knowledge, this is the first study of daily agricultural commodity price forecasting across many important commodities over a long period of time. Previous studies in this line of research include Xu and Zhang (2021), who focus on daily corn cash price forecasts across hundreds of spatially diverse markets in the United States through the neural network during 2006–2011. For soybean cash price forecasts, Klaussen and Uhrig (1994) investigate the use of the neural network during 1974–1993 for the Central Illinois market in the United States. Ayankoya et al. (2016) explore the neural network for daily white maize spot price forecasting on the Johannesburg Stock Exchange in South Africa during 2010–2015. George et al. (2022) study the neural network for forecasts of the Nifty 50 index during 2011–2019. Moody et al. (1998) research reinforcement learning for trading systems and portfolios and demonstrate predictabilities of the advanced method through simulations using the monthly S&P 500 stock index during 1970–1994. Zarkias et al. (2019) also propose the advanced approach of reinforcement learning for financial trading and illustrate its usefulness with the euro–US dollar exchange rates during 2007–2015. For multi-commodity work, Wang et al. (2017) examine neural network-based hybrid models for daily Chicago Board of Trade wheat, corn, and soybean futures price forecasts during 2010–2016. Ma et al. (1990) focus on futures price adjustment processes responding to significant events across different agricultural and financial contracts through the autoregressive integrated moving average process during periods ranging from 3 to 13 years. In a relevant line of research on forecasting price directions, Park and Irwin (2010) investigate the profitability of technical trading rules in 17 US futures markets during 1985–2004, which cover contracts for grains, meats, soft metals, energy, currencies, interest rates, and an equity index. Banga and Brorsen (2019) study the profitability of technical analysis through both machine learning approaches, such as neural networks, decision trees, and random forests, and statistical methods, such as logistic regressions, for commodities from agricultural, livestock, financial, and foreign exchange futures markets with daily data during 1969–2016, 1977–2016, 1982–2016, and 1974–2016, respectively. Park and Irwin (2007) and Park and Irwin (2011) offer comprehensive discussions about the profitability of technical analysis. The forecasting framework presented here is easy to implement and has the potential to be generalized to other commodities. This study contributes to forecasting users' information needs for decision-making. Our results can also be combined with fundamental forecasts in forming perspectives of commodity price trends and conducting policy analysis.

2 | DATA

Daily agricultural commodity price data, sourced for analysis from Macrotrends, for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat, are shown in Figure 1, together with their first differences. These are futures contract prices, and all contracts are front-month contracts. Prices are calendar-weighted adjusted, with contracts rolling on the first of the month, forming the continuous contract history. The calendar-weighted method allows for a smooth transition from one contract to the next by using blended or weighted-average combined prices during a predetermined transition window right around the roll date. This method is a compromise between the forwards Panama Canal method and backwards Panama Canal method. The first day of the month as the roll date rule and calendar-weighted rolling as the price adjustment rule are perfectly deterministic, predictable, and smooth, and they do not contaminate economic aspects of the price history, making the resultant series appropriate for economic forecasting purposes (StevensAnalytics, 2022). The small advantage of the neural network model found in this work as compared to the no-change model could be due to this particular price adjustment since the adjusted series will contain the mean reversion and the seasonality that is in the cash prices (Maples & Brorsen, 2022). It is worth noting that these futures markets have price limits, and not adjusting for price limits is a limitation of this work. Prices for coffee (dollar per pound) range from August 20, 1973 to August 10, 2021, those for corn (dollar per bushel) from July 1, 1959 to August 10, 2021, those for cotton (dollar per pound) from August 22, 1972 to August 10, 2021, those for oats

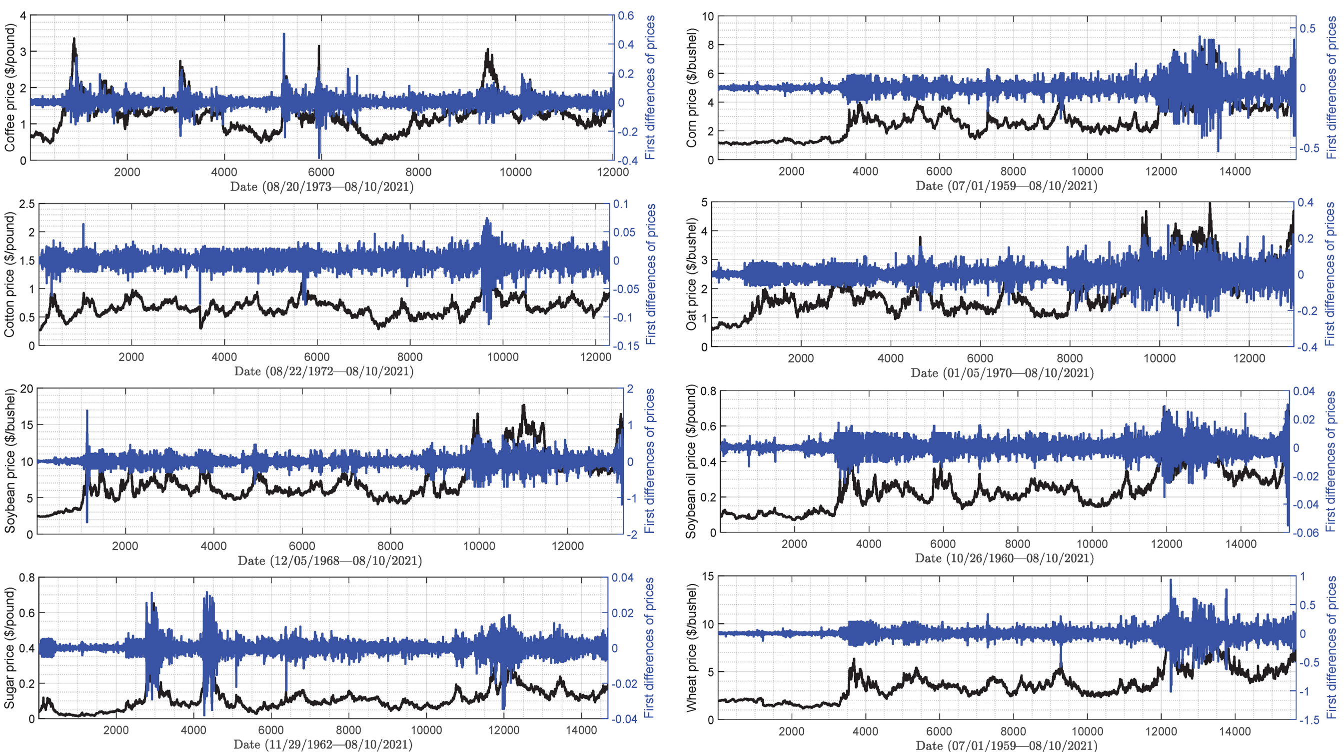

FIGURE 1 Daily prices and their first differences for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

(dollar per bushel) from January t, 1970 to August 10, 2021, those for soybeans (dollar per bushel) from December 5, 1968 to August 10, 2021, those for soybean oil (dollar per pound) from October 26, 1960 to August 10, 2021, those for sugar (dollar per pound) from November 29, 1962 to August 10, 2021, and those for wheat (dollar per bushel) from July 1, 1959 to August 10, 2021. There are a total of 12,029, 15,649, 12,300, 12,997, 13,265, 15,301, 14,684, and 15,650 observations for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat, respectively, covering periods of 49, 63, 50, 52, 54, 62, 60, and 63 years. Table 1 shows summary statistics of the data. We could observe that they are not normally distributed, which is generally expected for financial series. Figure 2 plots the data using histograms of 20 bins and kernel estimates to show their distributions.

3 | METHOD

We explore nonlinear autoregressive (NAR) models for price forecasting of eight agricultural commodities, including coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. The NAR model can be expressed as $x_t = f(x_{t-1}, \ldots, x_{t-d})$, where x represents the price of a

TABLE 1 Summary statistics of daily prices and their first differences of coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

Commodity	Series	Minimum	Mean	Median	Maximum	Standard deviation	Skewness	Kurtosis	Jarque–Bera *p*-value
Coffee	Price ($/pound)	0.4250	1.2589	1.2325	3.3563	0.4732	0.8663	4.2187	<0.001
	First difference	−0.3840	0.0001	0.0000	0.4700	0.0311	0.2544	18.8534	<0.001
Corn	Price ($/bushel)	1.0070	2.7412	2.5175	8.3125	1.3513	1.3469	5.2766	<0.001
	First difference	−0.5300	0.0003	0.0000	0.4275	0.0509	−0.2077	15.3980	<0.001
Cotton	Price ($/pound)	0.2660	0.6768	0.6565	2.1414	0.1833	2.2854	15.9363	<0.001
	First difference	−0.1126	0.0001	0.0000	0.0741	0.0118	−0.4975	11.3939	<0.001
Oats	Price ($/bushel)	0.5820	1.9056	1.6675	4.9605	0.8171	0.9739	3.3743	<0.001
	First difference	−0.2825	0.0003	0.0000	0.2700	0.0399	−0.1247	7.6642	<0.001
Soybeans	Price ($/bushel)	2.3750	7.3434	6.5320	17.6825	2.8913	0.9489	3.6794	<0.001
	First difference	−1.6750	0.0008	0.0025	1.3800	0.1251	−0.4156	12.0896	<0.001
Soybean oil	Price ($/pound)	0.0697	0.2418	0.2295	0.7208	0.1177	1.0405	4.2678	<0.001
	First difference	−0.0550	0.0000	0.0000	0.0299	0.0044	−0.2297	10.6361	<0.001
Sugar	Price ($/pound)	0.0125	0.1119	0.0988	0.6520	0.0689	1.7612	8.4503	<0.001
	First difference	−0.0381	0.0000	0.0000	0.0315	0.0036	−0.5513	19.5217	<0.001
Wheat	Price ($/bushel)	1.1710	3.6789	3.4675	12.8250	1.6678	1.0036	4.3371	<0.001
	First difference	−1.0140	0.0003	0.0000	0.9300	0.0790	−0.0969	18.7523	<0.001

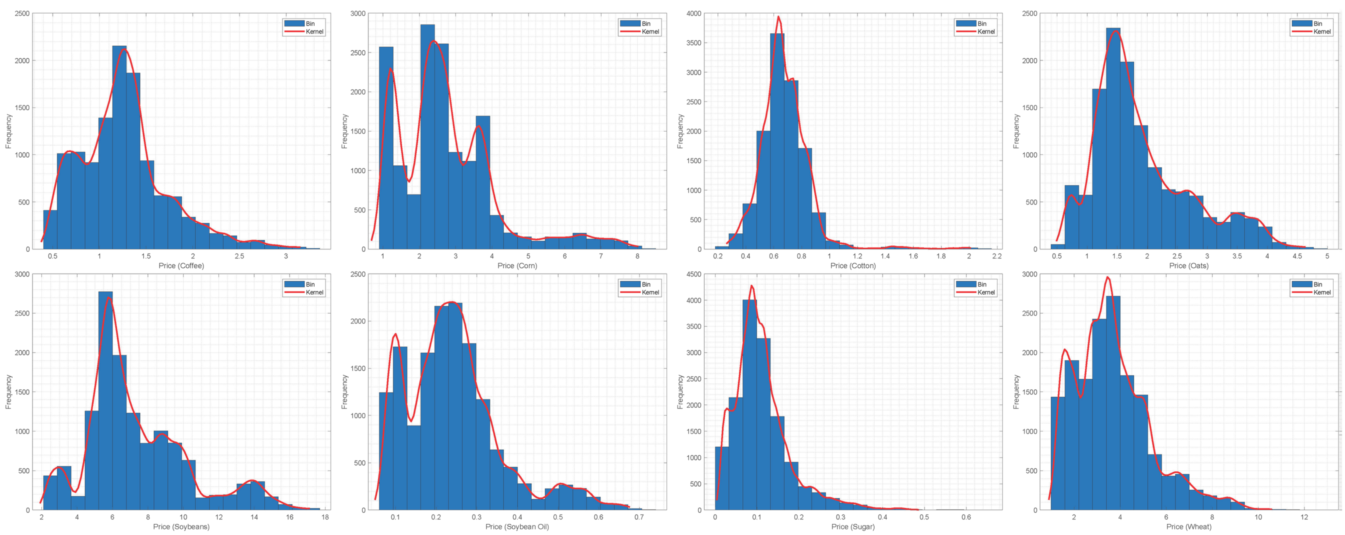

FIGURE 2 Distributions of daily prices of coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

specific commodity under consideration, t indexes time, d denotes the number of delays, and f stands for the function. We concentrate on one-day ahead short-term forecasts.

We adopt the NAR model based upon a two-layer feedforward network, which contains a logistic sigmoid transfer function in the form of $\phi(z)=\frac{1}{1+e^{-z}}$ for the hidden layer and a linear transfer function for the output layer. It might be worth noting that the output x_t is fed back via delays to the input of the network, and model training would be in the form of open loops for efficiency, in which the true output is utilized instead of feeding back the one estimated. In particular, adopting the open loop could ensure that the input to the feedforward network is more accurate, and the resultant network would possess an architecture that is pure feedforward.

Our final forecast models are based on three hidden neurons and four delays for coffee, eight hidden neurons and six delays for corn, two hidden neurons and two delays for cotton, three hidden neurons and five delays for oats, two hidden neurons and three delays for soybeans, two hidden neurons and five delays for soybean oil, eight hidden neurons and two delays for sugar, and eight hidden neurons and three delays for wheat. We adopt the Levenberg–Marquardt (LM) algorithm (Levenberg, 1944; Marquardt, 1963) to estimate the models and split the data for training, validation, and testing based on the ratio of 60% *vs* 20% *vs* 20%.

The LM algorithm aims at approximating the second-order training speed to avoid computing the expensive Hessian matrix, H (Paluszek & Thomas, 2020). The approximation can be expressed as $H=J^TJ$, where $J=\left[\frac{\partial f}{\partial x_1}\ \frac{\partial f}{\partial x_2}\right]$ for a nonlinear function $f(x_1,x_2)$ with $H=\begin{bmatrix}\frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2}\\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2}\end{bmatrix}$. $\mathbf{g}=\mathbf{J}^\mathbf{T}\mathbf{e}$ represents the gradient, and e represents the error vector. The rule $x_{k+1}=x_k-\left[J^TJ+\mu I\right]^{-1}J^Te$ is adopted for updating weights and biases, where I denotes the identity matrix. The algorithm would be similar to Newton's approach when $\mu=0$, and it would turn to be gradient descent with small step sizes when μ is large. μ would be decreased because of less need for faster gradient descent after successful steps. The LM algorithm possesses not only good attributes of steepest-descent algorithms and Gauss–Newton methods but also avoids many of their limitations. In particular, it can efficiently deal with the slow convergence issue (Hagan & Menhaj, 1994).

There are different algorithms available to train the model. Here, we also consider the scaled conjugate gradient (SCG) algorithm (Møller, 1993). The SCG and LM algorithms have been investigated in different fields (Doan & Liong, 2004; Kayri, 2016; Khan et al., 2019; Selvamuthu et al., 2019). Baghirli (2015) and Al Bataineh and Kaur (2018) provide comparative studies of these algorithms.

Backpropagation algorithms conduct weight adjustments in the steepest descent as the performance function would decrease in the direction rapidly, which, however, does not always represent the fastest convergence. Conjugate gradient algorithms conduct searches along the conjugate direction, which generally lead to quicker convergence than the steepest descent. Most algorithms make use of learning rates to determine the length of the updated weight step size. For conjugate gradient algorithms, step sizes are modified during iterations. Therefore, the search is conducted along the conjugate gradient direction to determine the step size for reducing the performance function. To avoid line searches in conjugate gradient algorithms, which are time-consuming, the SCG algorithm could be taken into consideration, which is fully automated and supervised and is faster than the LM backpropagation.

Finally, in reaching our final chosen aforementioned models, we also explore different model settings over delays, hidden neurons, and data-splitting ratios in addition to algorithms. In particular, we examine delays of two, three, four, five, and six, hidden neurons of two, three, five, and eight, and data-splitting ratios of 60% *vs* 20% *vs* 20%, 70% *vs* 15% *vs* 15%, and 80% *vs* 10% *vs* 10% for training, validation, and testing. Thus, given the data-splitting ratio and algorithm, the parameters in the neural network models are the delay and hidden neuron. The selection of the neural network parameters only involves the training and validation portions. In other words, they have been "seen" by the model. The testing portion is not involved in the selection of the parameters and is only used to test the model arrived at based on the training and validation portions. The magnitude of the gradient and the number of validation checks are utilized for terminating training. The gradient would become rather small as training reaches a minimum of performance. If the magnitude of the gradient is smaller than 10^{-5}, training would stop. The number of validation checks reflects the number of successive iterations for which validation performance fails to decrease. The number of validation checks used here is six, and training would stop if it is reached. In addition, if the number of training epochs (or iterations) reaches 1,000, training would stop as well. For the LM algorithm, the initial μ used is 0.001, the decrease (increase) factor for μ used is 0.1 (10), and the maximum value for μ used is 1,010. For the SCG algorithm, the Marquardt adjustment parameter used is 0.005, the weight change determinant for the second derivative approximation used is 5×10^{-5}, and the parameter for regulating the indefiniteness of the Hessian is 5×10^{-7}. Table 2 shows all explored model settings, where setting #55 is utilized to construct our final chosen forecasting model for coffee, setting #79 for corn, setting #41 for cotton, setting #57 for oats, setting #43 for soybeans, setting #47 for soybean oil, setting #71 for sugar, and setting #73 for wheat.

4 | RESULTS

We run all model settings in Table 2 for the prices of each of the eight agricultural commodities: coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. For a specific commodity and model setting, we calculate the relative root mean square error (RRMSE) as the performance metric across training, validation, and testing phases and present the results in Figure 3. In each subfigure of Figure 3, the commodity under consideration is indicated with pink font, the horizon axis "setting" corresponds to explored model settings listed in

		Model setting	
Algorithm	LM	$1 + 2i$	$i = 0,1, \ldots,59$
	SCG	$2 + 2i$	
Delay	2	$1 + 10j$–$2 + 10j$	$j = 0,1, \ldots,11$
	3	$3 + 10j$–$4 + 10j$	
	4	$5 + 10j$–$6 + 10j$	
	5	$7 + 10j$–$8 + 10j$	
	6	$9 + 10j$–$10 + 10j$	
hidden neuron	2	$1 + 40\,k$–$10 + 40\,k$	$k = 0,1,2$
	3	$11 + 40\,k$–$20 + 40\,k$	
	5	$21 + 40\,k$–$30 + 40\,k$	
	8	$31 + 40\,k$–$40 + 40\,k$	
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	

TABLE 2 Explored model settings for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

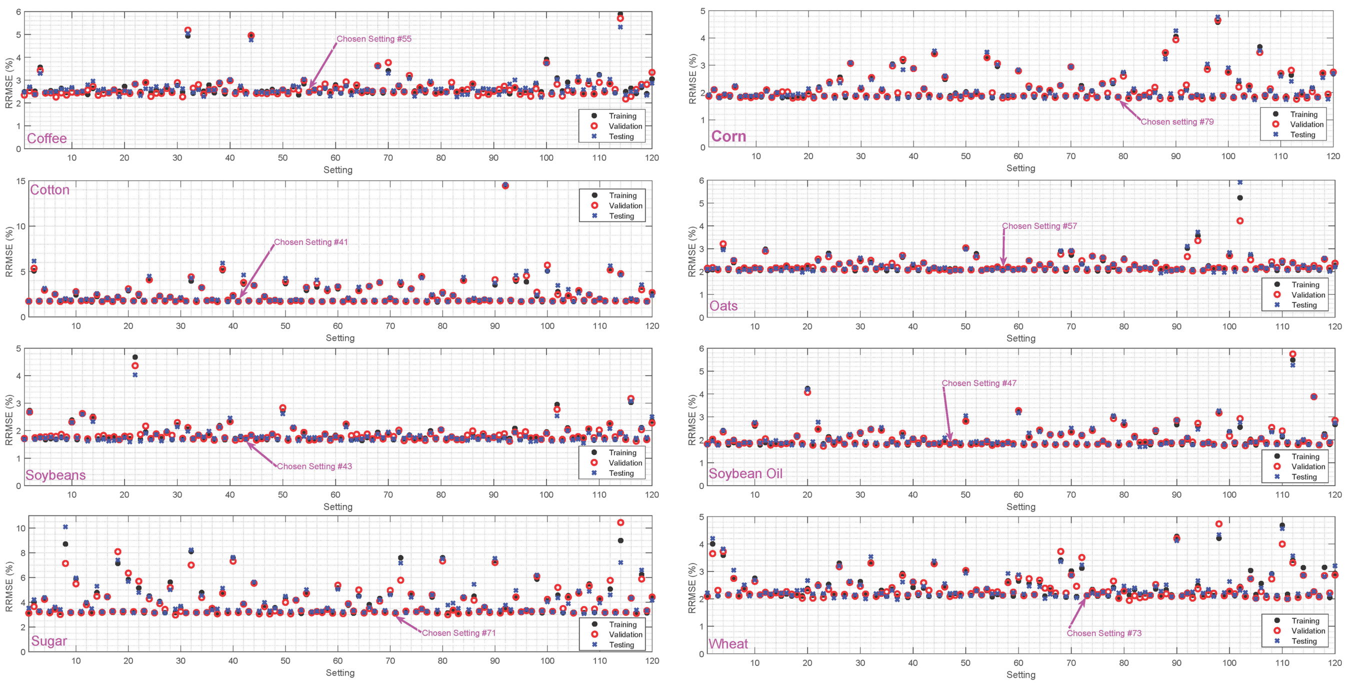

FIGURE 3 RRMSEs across all model settings for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. In each subfigure, the dark asterisk, red circle, and blue cross show the RRMSEs associated with training, validation, and testing, respectively.

Table 2, and the vertical axis "RRMSE (%)" shows the RRMSEs calculated for each model setting across training, validation, and testing. Balancing model performance and stability, we arrive at setting #55 (three hidden neurons and four delays) for coffee, #79 (eight hidden neurons and six delays) for corn, #41 (two hidden neurons and two delays) for cotton, #57 (three hidden neurons and five delays) for oats, #43 (two hidden neurons and three delays) for soybeans, #47 (two hidden neurons and five delays) for soybean oil, #71 (eight hidden neurons and two delays) for sugar, and #73 (eight hidden neurons and three delays) for wheat. These chosen settings are indicated with pink arrows in Figure 3 and are all based on the LM algorithm and the data-splitting ratio of 60% *vs* 20% *vs* 20% for training, validation, and testing. More specifically, taking coffee, for example, we could see from Figure 3 that setting #55 not only leads to rather low RRMSEs but also results in close RRMSEs (i.e., the dark dot associated with training, the red circle associated with validation, and the blue cross associated with testing nearly overlap each other for setting #55). There are other settings showing a lower RRMSE than setting #55 for coffee for a specific subsample but higher RRMSEs for the remaining subsamples, meaning a lower stability. For example, setting #53 has a slightly lower RRMSE than setting #55 for coffee for training but higher RRMSEs for validation and testing. Choosing the model setting with relatively stable performance across training, validation, and testing could help prevent overfitting or underfitting.

With chosen settings for prices of the eight commodities, we analyze sensitivities of performance to different settings by changing one setting each time and present the results in Figure 4, where RRMSEs for training, validation, and testing based on each setting are displayed. Taking coffee, for example, the comparison between settings #55 and #50 tests the sensitivity to the algorithm, between setting #55 and settings #51, #53, #57, and #59 the sensitivity to the delay, between setting #55 and settings #45, #65, and #75 the sensitivity to the hidden neuron, and between setting #55 and settings #15 and #95 the sensitivity to the data-splitting ratio. These results support setting #55 as the final choice for coffee, leading to RRMSEs of 2.46%, 2.47%, and 2.48% for the training, validation, and testing phases, respectively. We could observe from Figure 4 that setting #55 leads to the most stable performance across training, validation, and testing among the alternatives for coffee. From Figure 4, it could be seen that the performance is generally sensitive to the algorithm used, which is reflected through the comparison between setting #55/#79/#41/#57/#43/#47/#71/#73 that is based on the LM algorithm and

FIGURE 4 Sensitivities of model performance (the relative root mean square error) to different model settings for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

#56/#80/#42/#58/#44/#48/#72/#74 that is based on the SCG algorithm for coffee/corn/cotton/oats/soybeans/soybean oil/sugar/wheat. This is consistent with Batra's (2014) work, which finds that while the SCG algorithm is generally better in terms of speed than the LM algorithm on a multilayer perceptron structure with two hidden layers, the LM algorithm generally leads to slightly better performance in terms of accuracy than the SCG algorithm. Figure 5 presents RRMSEs for the training, validation, and testing phases for all eight commodities based on chosen model settings. The chosen setting leads to RRMSEs of 1.85%, 1.83%, and 1.85% for the training, validation, and testing phases, respectively for corn; RRMSEs of 1.71%, 1.70%, and 1.72% for cotton; RRMSEs of 2.08%, 2.09%, and 2.05% for oats; RRMSEs of 1.70%, 1.72%, and 1.69% for soybeans; RRMSEs of 1.81%, 1.80%, and 1.81% for soybean oil; RRMSEs of 3.21%, 3.12%, and 3.18% for sugar; and RRMSEs of 2.12%, 2.12%, and 2.13% for wheat. We observed that results for training, validation, and testing performance were rather close to each other across the eight commodities. This is because the neural network model is largely finding the no-change model. Specifically, Table 3 reports overall RRMSEs based on neural network models and no-change models across the eight commodities, where the RRMSE based on the no-change model for a certain commodity is approximated as the standard deviation of its first difference series divided by the mean of its price series shown in Table 1 given that the mean of the first difference series is nearly zero across the eight commodities. From Table 3, we can see that overall performance based on the neural network model is close to that based on the no-change model across the eight commodities, although the former slightly outperforms the latter.

Overall, the chosen settings lead to accurate and stable performance across commodities, suggesting the usefulness of the neural network for forecasting their prices. We have conducted error autocorrelation analysis as well (details available upon request) and autocorrelations associated with different lags up to the lag of 20 are all within the 95% confidence limits across the eight commodities except for several sporadic lags, for which slight breaches of the confidence limits are found. These slight breaches will be avoided if the 99% confidence limits are used. The error autocorrelation analysis thus generally suggests that the chosen settings are adequate.

Nonlinearities in higher moments of financial and economic time series are well established in the literature (Karasu et al., 2020; Wang & Yang, 2010; Yang et al., 2010, 2008). The BDS test (Brock et al., 1996), for which one might refer to Dergiades et al. (2013) and Fujihara and Mougoué (1997) for a formal description and to Brock et al. (1996) for all technical details, confirms nonlinearities in prices of the eight commodities examined here, with $p-$values of the tests well below 0.01 and almost being 0 based on embedding dimensions of 2 to 10 and ϵ values (i.e., distance used for testing proximity of data points) of 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0 times the standard deviation of the price series. Neural network models are capable of self-learning for forecasting (Karasu et al., 2020) and capturing nonlinearities (Altan et al., 2021) that often inhabit financial and economic time series, such as prices of the eight commodities considered here. One great advantage of neural networks over other nonlinear models for time series is that a class of multilayer neural networks could well approximate a large class of functions (Wang & Yang, 2010; Yang et al., 2010, 2008). Rather than using a specific nonlinear function between inputs and the output for common nonlinear models, the basic structure of neural networks can combine many 'basic' nonlinear functions via the multilayer structure. With

TABLE 3 Overall RRMSEs for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat based on neural network models and no-change models

Commodity	Neural network (%)	No-change model (%)
Coffee	2.47	2.47
Corn	1.84	1.86
Cotton	1.71	1.74
Oats	2.08	2.09
Soybeans	1.70	1.70
Soybean oil	1.81	1.82
Sugar	3.19	3.22
Wheat	2.12	2.15

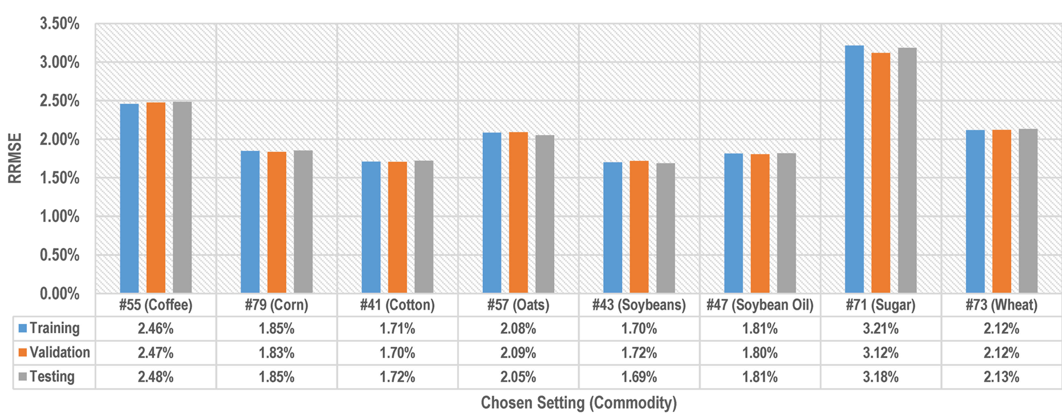

FIGURE 5 Model performance (the relative root mean square error) based on chosen model settings for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat

TABLE 4 Relative root mean square errors for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat across different folds (blocks)

Commodity	Testing fold 1	Training folds 2–6	Overall	Testing fold 2	Training folds 1 & 3–6	Overall	Testing fold 3	Training folds 1–2 & 4–6
Coffee	3.06%	2.48%	2.61%	2.33%	2.57%	2.53%	3.99%	2.41%
Corn	2.45%	2.19%	2.26%	2.03%	2.33%	2.31%	1.44%	2.16%
Cotton	1.41%	1.78%	1.71%	1.30%	1.85%	1.77%	1.40%	1.87%
Oats	2.53%	2.77%	2.79%	1.61%	2.72%	2.61%	2.39%	2.65%
Soybeans	5.52%	1.58%	2.14%	2.99%	2.50%	2.58%	3.25%	1.73%
Soybean Oil	1.49%	2.44%	2.51%	2.40%	2.49%	2.48%	1.72%	2.27%
Sugar	8.78%	3.17%	3.51%	9.36%	2.58%	5.75%	4.14%	3.19%
Wheat	1.05%	2.38%	2.41%	2.58%	2.59%	2.60%	1.31%	2.37%

TABLE 4 (Continued)

Commodity	Overall	Testing fold 4	Training folds 1–3 & 5–6	Overall	Testing fold 5	Training folds 1–4 & 6	Overall	Testing fold 6	Training folds 1–5	Overall
Coffee	2.66%	2.95%	2.49%	2.55%	2.40%	2.59%	2.56%	2.28%	2.50%	2.46%
Corn	2.07%	1.45%	2.14%	2.05%	2.28%	2.75%	2.66%	1.87%	1.77%	1.89%
Cotton	1.79%	1.66%	1.76%	1.75%	2.66%	1.68%	1.93%	1.41%	1.78%	1.72%
Oats	2.63%	2.29%	2.46%	2.45%	2.17%	2.86%	2.70%	1.87%	2.11%	2.08%
Soybeans	1.97%	3.08%	1.76%	1.95%	2.17%	1.89%	2.00%	1.32%	1.86%	1.73%
Soybean Oil	2.21%	1.28%	2.37%	2.25%	1.93%	2.96%	2.73%	1.44%	1.93%	1.81%
Sugar	3.31%	2.77%	3.40%	3.33%	3.59%	3.56%	3.59%	1.74%	3.72%	3.28%
Wheat	2.24%	1.66%	2.47%	2.37%	4.82%	4.62%	4.70%	1.91%	2.16%	2.13%

good performance achieved here, we empirically demonstrate the usefulness of neural network models for forecasting problems of prices of the eight commodities. The overall RRMSEs based on chosen settings for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat are 2.47%, 1.84%, 1.71%, 2.08%, 1.70%, 1.81%, 3.19%, and 2.12%, respectively. It is worth noting that some price analysts are more interested in forecasts of price changes as compared to price levels. There are certain areas for which forecasts of price levels could be important as well, such as financial model development and risk management in different financial institutions. Analysts in these areas could be interested in forecasts of prices in addition to forecasts of price changes. Generally, if price changes are forecasted, they can be converted to forecasts of prices. And if prices are forecasted, they can be converted to forecasts of price changes. The conversions might introduce some addition biases. In the literature, there are many studies on price change forecasts and many studies on price forecasts. The current study focuses on forecasts of prices. Our results might be used on a standalone basis or combined with other fundamental forecasts in forming perspectives of commodity price trends and conducting policy analysis. The forecast framework here is not difficult to implement, which is important for decision-makers (Brandt & Bessler, 1983), and might have potential to be generalized to price forecasts for other commodities.

5 | BENCHMARKING

We carry out benchmarking against an autoregressive integrated moving average process, ARIMA(1,1,1), for the eight agricultural commodities considered here in terms of forecast performance associated with the testing phase. We employ a modified Diebold–Mariano (Diebold & Mariano, 1995) test by Harvey et al. (1997) to facilitate comparisons of forecasts from different models. The modified test could help mitigate several potential shortcomings in the original test, including the oversized issue. The test is based upon $d_t = \left(error_t^{M_1}\right)^2 - \left(error_t^{M_2}\right)^2$ for the horizon h ($h = 1$ for our case), where $error_t^{M_1}$ and $error_t^{M_2}$ are forecast errors from models M1 and M2 that are indexed at time t. Accordingly, the test statistic for forecast comparisons of M1 and M2 is: $MDM = \left[\frac{T+1-2h+T^{-1}h(h-1)}{T}\right]^{\frac{1}{2}}\left[T^{-1}\left(\gamma_0+2\sum_{k=1}^{h-1}\gamma_k\right)\right]^{-\frac{1}{2}}\overline{d}$, where T is the length of the series for testing, $\overline{d}$ the sample mean of d_t, $\gamma_0 = T^{-1}\sum_{t=1}^{T}\left(d_t-\overline{d}\right)^2$ is the variance of d_t, and $\gamma_k = T^{-1}\sum_{t=k+1}^{T}\left(d_t-\overline{d}\right)\left(d_{t-k}-\overline{d}\right)$ is the kth auto-covariance of d_t for $k = 1, \ldots, h-1$ and $h \geq 2$. Under the null hypothesis that mean squared errors produced by two models are equal, the *MDM* test follows a t-distribution with $T-1$ degrees of freedom.

For all of the eight commodities, the final specifications of neural networks mentioned in Section 4 lead to better performance than the ARIMA(1,1,1). The corresponding p-valueof the MDM tests across the eight commodities are all well below 0.01 and close to 0, suggesting statistically significant differences in forecast performance. It is worth noting that the ARIMA(1,1,1) models are not recursively estimated for forecasts in the benchmarking and its performance might not be as ideal as one might have expected.

One line of research on forecasting is to combine results from different models to diversify against uncertainties. And a model not performing as well compared to another might not mean that the model cannot contribute to good forecasts. For forecast combinations, different models would receive different weights, and a non-optimal individual model could still contribute to forecasts. One direction of interest to researchers is to combine linear models, such as the autoregressive integrated moving average process, and nonlinear models, such as the neural network, for constructing better forecasts. Donaldson and Kamstra (1996), Stock and Watson (1998) and Blake and Kapetanios's (1999) studies offer good examples in this direction.

6 | ROBUSTNESS

We test the robustness of the chosen choices of model settings through analyzing performance across different folds (blocks) for the eight commodities (e.g., Bergmeir & Benítez, 2012). As aforementioned, the settings are three hidden neurons and four delays for coffee, eight hidden neurons and six delays for corn, two hidden neurons and two delays for cotton, three hidden neurons and five delays for oats, two hidden neurons and three delays for soybeans, two hidden neurons and five delays for soybean oil, eight hidden neurons and two delays for sugar, and eight hidden neurons and three delays for wheat, whose training is based on the LM algorithm. The data for each commodity are now divided into six equal folds from the beginning to the end of the price series. The model for each commodity is then estimated using five of the six folds, and forecasting performance is evaluated using the remaining fold. Table 4 summarizes the performance for the eight commodities across different folds, from which we could observe that the chosen settings still lead to a rather accurate and stable performance. For each commodity, we also compare forecast results of different testing folds with those based on the ARIMA(1,1,1) model and find that the neural network leads to better performance, with $p-$values of the $\mathcal{MDM}$ tests all well below 0.01 and close to 0.

7 | CONCLUSION

Forecasting commodity prices is a key concern for market participants. In this study, we focus on forecasting problems in datasets of daily prices for eight agricultural commodities, including coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat, over periods of 49, 63, 50, 52, 54, 62, 60, and 63 years, respectively. We explore univariate neural network modeling over different model settings and arrive at chosen settings that lead to accurate and stable performance for each commodity. Specifically, all chosen models are constructed through the Levenberg–Marquardt algorithm (Levenberg, 1944; Marquardt, 1963) with a data-splitting ratio of 60% *vs* 20% *vs* 20% for training, validation, and testing phases and result in an overall relative root mean square error of 2.47% for coffee based on three hidden neurons and four delays, 1.84% for corn based on eight hidden neurons and six delays, 1.71% for cotton based on two hidden neurons and two delays, 2.08% for oats based on three hidden neurons and five delays, 1.70% for soybeans based on two hidden neurons and three delays, 1.81% for soybean oil based on two hidden neurons and five delays, 3.19% for sugar based on eight hidden neurons and two delays, and of 2.12% for wheat based on eight hidden neurons and three delays. Our results can be used on a standalone basis or combined with fundamental forecasts in forming perspectives of commodity price trends and conducting policy analysis. Our forecasting framework is easy to implement, which is important for decision-makers in agriculture (Brandt & Bessler, 1983), and has the potential to be generalized to more commodities. It would be of interest in future to investigate the potential of combining time series models and graph theory from the machine learning world for commodity price forecasting (Bessler & Wang, 2012; Kano & Shimizu, 2003; Shimizu et al., 2006, 2011; Shimizu & Kano, 2008). Exploring the economic significance of using neural network models for forecasting could also be a worthwhile avenue for future research (Wang & Yang, 2010; Yang et al., 2010, 2008).

COMPLIANCE WITH ETHICAL STANDARDS

No funding was received, and the authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Xiaojie Xu https://orcid.org/0000-0002-4452-1540

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